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Towards Disappearing User Interfaces in Ubiquitous Computing: Human Enhancement from Super Senses to The Sixth Sense

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A thesis submitted in partial fulfilment of the requirements
for the degree of Doctor of Philosophy
in the

Department of Biomedical Engineering
School of Biological Sciences

September, 2019

Declaration of Authorship

I declare that this thesis titled, 'Towards Disappearing User Interfaces in Ubiquitous Computing: Human Enhancement from Super Senses to The Sixth Sense' and the work presented in it are my own and the use of all material from other sources has been properly and fully acknowledged.

Terence Kam Luen HUI

Abstract

The traditional view of the human sixth sense has always been a myth. Scientists have uncovered additional human sensory systems above the five basic senses proposed by Aristotle two thousand years ago. However, there is still no replacement for the traditional sixth sense which is usually associated with the sense of the future or remote events, and the reason could be the fact that most people would like to acquire this power of perceiving the future. The discovery journey for the extra human senses has also enabled scientists to get a clearer picture of the human sensory systems and how they are connected to the outside world through physiology, psychology, neuroscience, bioengineering and many other related disciplines.

In parallel, the research and development of technology has also evolved from connecting computers to the connecting of people using a massive sensory network through the Internet of Things. Artificial intelligence has enabled the transformation of a digital communication between machines through a standard of protocols to an affective communication between machines and humans utilising a sense of emotions.

The present research investigates the feasibility of a possible solution to implement an artificial sixth sense for each individual connected to the Internet. The knowledge of computer science, electronic engineering, psychophysiology and biomedical engineering has been reviewed and studied. A conceptual framework is proposed to enhance the human senses through the association with the huge sensory system built on top of the Internet of Things. Missing technology has been hypothesised from the reviewing of literature where an immediate implementation is not yet ready. This hypothesis was proven by an experiment utilising *emotionWear* built from scratch as a framework for emotion recognition based on a proposed emotional response-stimulus synchronisation concept.

Acknowledgements

Studying on a PhD course may sometimes feel isolated and lonely, but the completion of the journey and the associated work would not have been possible without the unconditional and endless advice and support from many people. I would like to sincerely thank each and every one of them.

First of all, my gratitude goes to Professor R. Simon Sherratt for his continued encouragement, support, guidance and inspiration. His enlightenment enabled me to pursue a research topic I had never dreamed of, a research area that ignited my interest and absorbed my whole attention for the past three years.

My special thank goes to Professor Hamid Bolouri, former supervisor during my MSc study decades ago, who has been always supportive whenever I need an academic reference. Your kindness is always remembered and your help is highly appreciated.

I would also like to thank my friends and family members, especially Rev. Cindy Cheung, Rev. Stewart So, Mr. and Mrs. Kam, and our families back in Hong Kong, for their patience, understanding, and friendship.

I would especially like to say thanks to my wife Tina who has been extremely supportive of me throughout this entire study and has made countless sacrifices to help me get to this point.

Above all, I humbly extend the honour and glory to my Lord Jesus Christ for His richest grace and mercy for giving me the strength and wisdom to accomplish this thesis.

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Dedicated to my wife Tina

Chapter 1

Introduction

> Peter woke up in a rainy morning, got dressed and ready to work without having breakfast. He took his car key and got into his jeep ready to drive, a message on the dashboard screen suggested a new route avoiding all mountain roads for him driving towards his office. Peter had perceived fear emotion on climbing up the mountain for the last couple times during bad weather which could be the result of his previous car accident of sliding back against a guard rail on a slope in a rainy day. After finishing his working day with six stressful moments during meetings and interfacing with clients, he was leaving in a bad mood and a suggestion was sent to Peter's smartphone advising him to meet Mary who just came to town for work. The suggestion was based on a statistical analysis showing that the chance of Peter promoting happiness emotion with Mary was 92.8%. This is Peter's artificial sixth sense that always reminds him for future and remote contexts that may significantly affect his emotional behaviours.

1.1 Motivation

Human Computer Interaction (HCI) research deserves greater and more rigorous attention amid the drastic technological revolution during the recent decades in three major areas: (1) the Internet of Things (IoT) has become a network of computers and sensors around the globe, (2) the miniaturisation of silicon electronics enables embedded computers to be installed into everyday objects, and (3) the maturity of Artificial Intelligence (AI) has enforced computers to simulate and predict human emotions. If the human sixth sense, according to the folk concept, is a sense of predicting individual responses for remote or future environment (Macpherson, 2010), a statistical analysis of one's historical responses associated with the exposed contextual stimuli is adequate to build an individual artificial sixth sense system. This idea seems to be a straight forward approach to build a system using unnoticeable natural user interfaces for intuitive user response collection, and applying the latest IoT concept for ubiquitous data manipulation anywhere in the connected world, and finally adopting contemporary machine learning algorithm for statistical prediction of human emotions based on a ground-truth dataset collected and stored in the IoT cloud. The current research tries to exploit the technological readiness for building an artificial sixth sense for each connected individual based on the three major technologies mentioned above.

IoT facilitates the concept of ubiquitous and pervasive computing, and connects any network-enabled computers to share information through a universally agreed Transmission Control Protocol/Internet Protocol (TCP/IP) platform based on Machine-to-Machine (M2M) communications (Hui, Sherratt and Díaz-Sánchez, 2017). Wireless technologies play a major role in the computer connections extending wired networks to remote areas without the limitations of physical cables. Network of sensors, especially Wireless Sensor Networks (WSNs), have become vital members of the IoT with a fast-growing application area specialising in sensing the environments. Consequently, with a huge ubiquitous deployment of smart sensors (i.e. sensors having embedded computing devices) around the planet through IoT, any connected human will be able to extend individual sensory systems to an enhanced sensory system consisting of super sensors with higher sensitivity and better functionality not normally achievable by the human counterparts (Hui and Sherratt, 2017). The Internet of Senses (IoS), or the Internetworking of sensors, not only allows the sensing of human user responses whenever and wherever Internet connection is reached, but also enables the collection of the contexts promoting those responses. If these sensors are unnoticeable in nature and powerful in computing, a true intuitive responses and the associated context may be able to be registered onto a cloud storage for further data processing.

Miniaturisation of silicon electronics, doubles its density every two years as observed by the Moore's law in the past five decades, empowers the rapid development of embedded network-enabled computing devices to simultaneously boost their processing power and shrink their physical dimensions. A picture painted by Weiser as *"The Computer for the 21st Century"* has more or less been accomplished, and the concept keeps weaving disappeared technologies into the fabric of human daily life (Weiser, 1991). Interacting with disappeared computers has created a new challenge to traditional HCI technologies, thus Disappearing User Interfaces (DUIs) may be a better methodology for interfacing humans and computers with information contents similar to the natural human communications. DUI is therefore, a critical ingredient in the IoS supplying appropriate technologies with unnoticeable nature and an abundance of processing power for both sensing and analysing individual activities and the environments surrounding them continuously. Communication with contents, however, is not as straight forward as traditional computers using console type interfaces, a certain degree of computational analysis based on AI algorithm is involved in recognising the actual meanings of the contents.

The learning capability of AI lets computers understand human intentions by training. A statistical prediction of machine learning methodology applies AI to forecast human emotions which have been hypothesised as markers for decision making (Damasio, Everitt and Bishop, 1996), indicators for perception responses (Cacioppo, Tassinary and Berntson, 2007), and initiators for taking actions to the changing surrounding environments (Frijda, 2016). Decades of research in machine learning such as ground-truth data collection (Constantine and Hajj, 2102), feature extraction from database (Godin et al., 2015), and classification methodologies have contributed significant improvement in the prediction accuracy in human emotions using statistical analysis (Kragel and LaBar, 2014; Verma and Tiwary, 2014). However, the background knowledge from psychophysiology is also critical in linking and studying the relationship between psychology which understands human behaviours and physiology which shows the corresponding biological changes of the human bodies (Cacioppo, Tassinary and Berntson, 2007). The relationship between cognition, attention and emotion provides further insight into emotion recognition based on Orienting Response (OR) activities (Bradley, Keil and Lang, 2012; Wells and Matthews, 2014), and the autonomic specificity allows specific differentiation of basic discrete emotions through patterning of the concomitant emotional physiological signals (Kreibig, 2010).

Understanding the anatomical relationship between the visceral nervous system and the human brain empowers the application of estimating human behaviours through physiological measurements (Friedman, 2007; Critchley and Harrison, 2013; Landowska, 2014; Lang, 2014). The “Lie Detector” or “Polygraph” may not be the first application of emotion recognition using physiological signals, but it could be the most famous one (Smith, 2012).

Despite the controversy over the detection accuracy, applying the psychophysiological concepts in human and even animal emotion recognition has never ended (Panksepp, 2011; Jerritta et al., 2011; Healey, 2014; Ramzan et al., 2016). Autonomic Nervous System (ANS) specificity and the hypothesis of basic emotions (Ekman, 1992; Ekman, 2016) are still the background for recognising the different emotion states such as mood and stress (Friedman, 2007; Valenza et al., 2014; Greene, Thapliyal and Caban-Holt, 2016; D. S. Lee, Chong and B. G. Lee, 2017). Commercialisation of emotion recognition through human sensing is still at its early stage, but real life applications can be found persistently in both the academia and the industry (Ratsamee et al., 2013; Patwardhan and Knapp, 2017; Dobbins and Fairclough, 2017; Jiang et al., n.d.). Advance in scientific research together with the innovation in practical applications are the keys to unlock the true potential of AI in understanding and simulating human emotions.

The above technological revolutions motivate the current research to discover a novel human interaction experience with the IoT based on the sixth sense concept depicted in Figure 1.1.

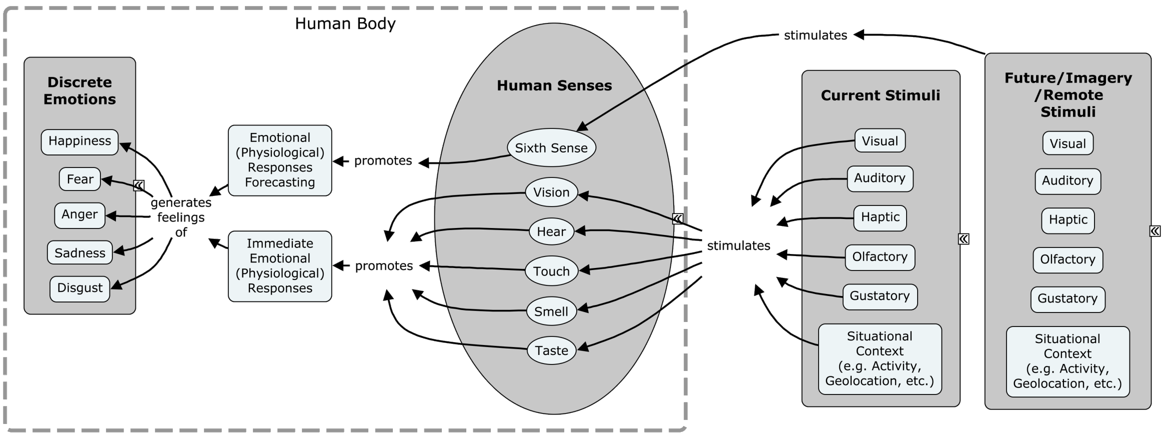

FIGURE 1.1: The Sixth Sense Concept

This sixth sense concept is based on the traditional model of stimulation, sensation and perception process for human emotion (Cacioppo, Tassinary and Berntson, 2007; Henshaw, 2012). Major stimuli coming outside of the human bodies can be roughly classified into visual, auditory, haptic, olfactory and gustatory stimuli which stimulate the human senses such as vision, hearing, touching, smelling and tasting senses. These local stimuli activate sensory transduction in the afferent neurons allowing the brain to decode the signals through sensation and promote the concomitant physiological responses which can be classified as basic emotions such as happiness, fear, anger, sadness and disgust (Levenson, 1992; Ekman, 1992). Human sixth sense, hypothesised as a prediction of the future, can be treated as the sense of predicting emotional responses stimulated by future or remote stimuli similar to the emotion perception process for local stimuli. Smart sensors for IoT enable an ubiquitous sensing capability which extends individual human senses to anywhere that an internet connection can reach. DUI allows the detection of human emotions intuitively through the capture of physiological responses and the associated stimuli. Machine learning, mimicking the human sixth sense, provides an effective tool for emotion recognition understanding human emotional behaviours by establishing a statistical model using experiential data as training dataset, and the responses initiated by remote and forecast stimuli become the prediction targets. An artificial sixth sense implementation seems to be ready based on the above mentioned contemporary technologies together with the hypotheses from psychophysiology.

The motivation of building an artificial sixth sense system has driven the current research to search for the necessary technologies acting as the building blocks of the system for individual human in an Internet of People (IoP) environment. Reviewing the required technologies is the groundwork but an investigation of the technological readiness is the major focus in this study. The following sections describe the hypothesis of what is the missing technology, how this research is designed, and how an experiment is conceived to discover and verify the hypothesis.

1.2 Hypothesis

"The synchronisation between emotional stimuli and the concomitant responses is the missing piece of technology in building an artificial sixth sense concept based on the IoT architecture."

The artificial sixth sense concept pulls existing technologies into a novel architecture implemented on top of the IoT. The internetworking of smart sensors enables the internetworking of connected people to effectively share and use information as contents. Additionally, AI enhances the ANS specificity and empowers computers to communicate with human users by decoding and encoding the contents for information exchange (Hui and Sherratt, 2017). The knowing of when and where human beings are experiencing emotional responses enables a statistical prediction classifier to be trained and used as an emotion predictor for future and remote context (i.e. the context of stimulation, including stimuli stimulating the human sensory systems, the current activities being performed, and the environment surrounding the human subjects). This is the "when" and "where" that needs to be synchronised with the promoted emotional responses in order to capture what exactly causes the emotional perception (see Chapter 6). Knowing these moments of true emotion elicitation is critical in (1) collecting the data for performing the pattern matching through the hypothesis of ANS specificity, and (2) collecting the contexts for future prediction through computational statistics. Therefore, the focus for verifying the current hypothesis relies on the timing of data and context collection instead of an accurate immediate and future emotion recognition itself. Despite AI is a major component in our artificial sixth sense concept for immediate emotion recognition and future emotion prediction, it is not included in the current study since AI may help increase the recognition and prediction accuracy through statistical analysis but it doesn't identify the moments to collect the emotional physiological responses which are critical for implementing a successful AI algorithm.

Sensing technologies have been extensively researched enabling the direct and indirect recognition of the environment that may stimulate the human sensory systems, such as visual, auditory, haptic, olfactory and gustatory. Psychophysiological research, similarly, has put enormous efforts proposing theoretical and practical hypotheses boosting the accuracy of emotion recognition. However, the detection of the moment that a contextual stimuli is eliciting a perception promoting an emotional response, particularly an emotional physiological response, is not obvious from previous research. A synchronisation between the emotional stimuli and the responses is crucial in analysing the elicitation moments for recognition and prediction of emotional behaviours.

1.3 Aims and Objectives

There are two primary aims of the current research. The first aim is the searching for an answer to the research question which is the title of this thesis "Towards Disappearing User Interfaces in Ubiquitous Computing: Human Enhancement from Super Senses to the Sixth Sense". Verification of the hypothesis in section 1.2 that contemporary technologies are not mature enough for a practical implementation is the second aim. Five objectives were set to support the achievement of the two aims:

(a) Investigation on IoT technologies

A survey of contemporary technologies being used in the IoT was conducted to investigate how the latest technological advancement helped shape the current Internet and the way each technology worked together to support the idea of automation. The “smart” nature of intelligently and autonomously connecting humans and computers on the Internet lays the groundwork for building a seamless integration on a single platform. The attention of this survey was focused on a taxonomy of IoT technologies, and a list of seven major requirements for building smart homes in smart cities was proposed. Finally, the result was published as a journal article with Springer[1].

(b) Investigation on intuitive human computer interaction

Miniaturisation of silicon electronics joins the IoT and provides disappeared computers ubiquitously and pervasively. The disappearing nature hinders a new challenge on HCI where traditional Command Line Interface (CLI) and Graphical User Interface (GUI) are no longer effective if not impossible to function as normal. Intuitive interaction with “content” seems to be the best way to rebuild the information exchange channel which pushes Natural User Interface (NUI) to the spotlight to become future de-facto standard. This investigation summarised and classified the different DUI technologies through a literature survey of recent HCI research suitable for ubiquitous computing environment, and how DUI enabled the extension of human senory systems to the huge IoS. The result was published as a journal article with Elsevier[2]. Together with the article produced in objective (a) above, these two published articles[1 & 2] achieve one part of the first aim of the present study by answering the research question that DUI can enhance the human sensory systems when human beings are network-connected to an ubiquitous computing environment, or the IoT. However, the second part of the research question, i.e. the sixth sense, was not fully answered.

[1] Hui, T. K. L., Sherratt, R. S. and Díaz-Sánchez, D. ’Major requiremens for building Smart Homes in Smart Cities based on Internet of Things technologies’. Future Generation Computer Systems 76. (2017), pp. 358-369.

[2] Hui, T. K. L. and Sherratt, R. S. ’Towards disappearing user interfaces for ubiquitous computing: human enhancement from sixth sense to super senses’. Journal of Ambient Intelligence and Humanized Computing 8.3 (2017), pp. 449-465.

(c) Investigation on emotion, attention and cognition

Emotion recognition using pattern matching seems to be the common architecture which utilises machine learning algorithm to build statistical models for prediction. Highly accurate prediction results have been achieved through numerous empirical research based on autonomic specificity hypothesis. Cross disciplinary review of research from psychology, neuroscience, psychophysiology, affective computing, and biomedical engineering enables a better understanding for the elicitation, capture, and recognition of emotions. A literature review was conducted mainly on psychology and psychophysiology focusing on human emotions and the associated research on cognition and attention. Section 2.3 summarises the multi-disciplinary review of related theorical and empirical research which laid down the groundwork for achieving the next two objectives.

(d) Design and implement an emotion recognition system

A novel emotion recognition framework was built from scratch based on the hypotheses and theories from multi-disciplinary research. The synchronisation between stimuli and the physiological responses is the major feature implemented in this platform. The framework, *emotionWear*, was built using common wearable biosensors and communicated wirelessly through Bluetooth Low Energy (BLE) to an Android smartphone, and the analysis was done by interactive Python (iPython). The background knowledge from the literature review of the last three objectives enabled the design of the *emotionWear* framework, and the whole design was depicted in details as part of a journal article published with MDPI[3].

(e) Conduct emotion recognition experiment using *emotionWear*

An experiment was conducted using the *emotionWear* framework by recruiting ten subjects to watch audiovisual stimuli. The stimuli and the corresponding physiological responses were recorded simultaneously such that a synchronised analysis could be performed using the iPython data science platform. Together with the contribution from the previous objective (d), the result of this experiment and the corresponding analysis and discussion completed the journal article and published with MDPI[3]. This article[3] is the combined effort from objectives (c - e) such that:

[3]Hui, T. K. L. and Sherratt, R. S. 'Coverage of emotion recognition for common wearable biosensors'. Biosensors 2017, 8(2), 30.

(i) the enhancement of the sixth sense for each connected human is possible once individual emotions can be recognised and predicted through the IoS, thus, the first aim of the present research is fully achieved;

(ii) the second aim of the present research is also successfully achieved by confirming the hypothesis with empirical evidence verifying that an emotional response-stimulus synchronisation technology is missing for an immediate engineering implementation of the artificial sixth sense concept.

1.4 Research Design

The current research is a multidisciplinary study including mainly electronic engineering, biomedical engineering, computer engineering, and psychophysiology. Acquiring new knowledge and learning common languages in multiple disciplines not only increase the burden for extensive literature review, but also elevate the risk of not following closely the latest research on multiple fields of study. Publishing the research results especially the early stages of literature review which acted as a feasibility study could help confirm the research direction and validate the concept for the present study. The peer review process in academic journals makes sure the study results submitted as manuscripts are up to the standard for contributing new knowledge on latest research of particular disciplines defined by the journals' scopes, thus, finding the right journals to publish is critical in serving our purposes. This strategy determined the design of the present research where the sixth sense concept was translated into several statements verified by the scholars of related academic fields. The following statements, closely linked to the premises on technological revolution described in the previous section, are the basis for building the proposed artificial sixth sense concept:

(a) IoT utilises the Internet to provide contemporary technologies to be available ubiquitously and pervasively such that it allows HCI to be more effective anytime and anywhere when IoT connectivity is reached.

(b) Natural user interface such as DUI empowers an intuitive interaction between humans and computers through contents such that both the stimuli and the concomitant human responses can be collected to form the basis for human sixth sense prediction.

(c) Coverage of emotion recognition using DUI on IoT can show the readiness of building an artificial sixth sense system based on contemporary technologies and the hypotheses from Psychophysiology.

New research projects normally start from a literature review and the current study is no exception. The review was conduced in three stages according to the steps for verifying the three statements listed above in chronological order, and the target academic areas for each review stage were chosen as follows:

(a) Stage 1 - IoT related technologies

  (i) Networking technologies: networking architecture, wired and wireless sensor networks, machine to machine communication, etc.

  (ii) Computing technologies: computer engineering, computer programming, cloud computing, ubiquitous and pervasive computing, etc

  (iii) HCI: machine to human interaction methodologies, user interface and user experience, etc.

  (iv) IoT: smart home/home automation, smart grid, smart cities, cybersecurity and privacy, etc.

(b) Stage 2 - NUI and DUI

  (i) Physiology: biomedical engineering, human senses, human perception, etc.

  (ii) Sensing technologies: sensors, biosensors, wearables, body area networks, etc.

  (iii) Computing technologies: computer input and output technologies, affective computing, etc.

  (iv) Sixth sense: psychology, philosophy, etc.

(c) Stage 3 - Emotion recognition

  (i) Emotion: psychology, psychophysiology, affective computing, neuroscience, etc.

  (ii) Biological sensing: biosensors, human senses, biological sensing technologies, etc.

  (iii) Emotion recognition: psychophysiology, artificial intelligence, machine learning, biomedical engineering, computer engineering, IoT, etc.

The target of this literature review was to achieve the aims described in section 1.3, and the review process had also assisted the current study in verifying the research topic through a feasibility study, defining the method in executing the experiment, limiting the scope of study and clarifying the necessity of ethical consideration.

1.4.1 Feasibility study

An artificial sixth sense concept seems to be a straight forward approach for integrating contemporary technologies on a single platform which extends individual human senses to a much bigger Internet-enabled sensory system involving superior and ubiquitous sensors throughout the worldwide IoT network. A position paper (Hui and Sherratt, 2017) acting as the output of the feasibility study of the current research, established a sixth sense concept showing the relationship between major IoT technologies (Hui, Sherratt and Díaz-Sánchez, 2017) and the human interactions (Hui and Sherratt, 2017). This position paper also answered the research question illustrating that human sixth sense was the result of an enhancement through ubiquitous computing and natural user interfaces.

The research in human sixth sense when it refers to extrasensory perception has always been treated as pseudoscience, unless a clear definition is given where scientific facts are linked and the scope of applications is restricted (Stonefoot and Clyde, 2004; Gordin, 2017). Assumption was made linking the human sixth sense to the sense of future individual emotion prediction which was closely related to emotional context awareness. IoT provides ubiquitous and pervasive technologies empowering the interaction of humans and the situational contexts wherever Internet connection is reached, extension for human emotion prediction is then possible with remote or future contexts using computational statistics or machine learning. All these assumptions were based on concurrent research through literature review and was the basis for building the concept of artificial sixth sense. IoT is the platform providing the required contemporary technologies for building context awareness, and DUI is the necessary interaction technologies for intuitive and natural communication in situational contexts between humans and computers. This was the feasibility study of the artificial sixth sense concept through literature research and the results were published in academic journals to verify that the concept was valid and it was contributing new knowledge in applying DUI on IoT for establishing a human sixth sense platform. Chapter 3 and Chapter 4 show the feasibility study translated into two papers published in the academic journals. The first paper in Chapter 3 provides a background for integrating contemporary technologies on a common platform established by the IoT concept, and presents how different technologies can be combined to facilitate various applications such as smart homes and smart cities. The second paper in Chapter 4 is the position paper illustrating how human senses can be enhanced and how the human sixth sense can be simulated based on the ubiquitous computing platform described in the first paper.

1.4.2 Research method

After publishing the position paper which confirmed the proposed sixth sense concept, focus was directed to an experiment verifying the hypothesis that an artificial sixth sense system was not ready due to the missing technology in response-stimulus synchronisation. The core of the experiment relied on a novel emotion recognition platform which tried to detect true emotions from a controlled emotion elicitation method. Despite a plethora of research on emotion recognition, there is no standard procedure nor method ever defined and generally agreed. The complication starts with the types of stimulation, the novelty and significance of the stimuli, the individual response specificity, the personal health conditions, the various situational contexts, and many other factors that will subtly affect the emotional responses promoted by the same conditioned and unconditioned stimuli. The literature review listed out the common methods and ultimately one was chosen that could be easily repeatable and supported by references that most researchers agreed. Major components for building the proposed emotion recognition framework (the "*emotionWear*") to verify the hypothesis have been selected according to the literature review and they are:

(a) Stimulation for emotion elicitation using affective pictures from the IAPS (International Affective Picture System) (Lang and Bradley, 2007) and short film clips from previous research with rating references (Gross and Levenson, 1995; Schaefer et al., 2010) as visual and audio stimuli.

(b) Biological signal collection devices using wearable biosensors for measuring physiological responses. Focus was put on three vital signals which indicated the variations in heart rate, electrodermal activity, and fingertip temperature.

(c) Natural user interfaces embedded in a sensing glove for computer inputs and a Virtual Reality (VR) headset for computer outputs. A smart phone acted as a central controller synchronising between the inputs and outputs according a predefined algorithm.

(d) Data collection and analysis architecture based on wireless data communication (e.g. WiFi, BLE, etc.) empowering the smart phone to also act as a bridge packaging and uploading all sensor data to a cloud storage for further processing. A data analysis package based on iPython was used to examine the data according to a set of hypotheses from previous psychophysiological research.

The details of the research method and the component selection process for the *emotionWear* according to the literature review is presented in Chapter 5.

1.4.3 Scope and limitations

The concept design of an artificial sixth sense could be done through a literature review but the experiment for verifying the hypothesis of missing technology in the proposed concept required the building of a framework including all necessary hardware and software. Although no standard methodology for human emotion recognition was academically agreed, there were many methods and procedures proposed from previous studies illustrating the different areas of applications for emotion recognition in various situational contexts. Limitation of the scope for the framework in the current experiment was required to focus all necessary resources to the target for achieving the predefined aims and meeting the schedule for a three-year PhD study. According to previous psychophysiological research, a simple emotion recognition platform which acted as the core element in the proposed artificial sixth sense concept, could be setup with the basic components listed in the Research Method (section 1.4.2). However, many optional elements for widening the application and enhancing the accuracy were removed from the scope of the present research . The reasons for not including those optional components and elements in our experiment are as follows:

(a) Stimuli were chosen only from static pictures and short film clips
Any stimulus, conditioned or unconditioned, may be able to stimulate the human senses and activate an emotional perception when the stimulation meets the novelty and significant criteria for each Individual Response Specificity (IRS). Multiple stimuli could make the perception more complicated, thus, simple types of stimuli was

chosen to be used in a controlled environment for easy analysis. Previous references are also critical for standard stimuli such that known responses can be expected and referenced. Finally, 20 static pictures as visual only stimulation with reference rating were chosen from IAPS, and 10 short film clips from previous studies as visual plus auditory also with rating were selected as stronger stimulation for comparison purpose.

(b) Stimulation of emotion was conducted via a VR headset

A controlled environment that could restrict the exposure to unintended stimulation was setup through a VR headset which enabled a full capture of the test subject's visual and hearing senses. Bespoke application software was written to simultaneously fit the stimulation contents to the test subjects and collect their physiological responses.

(c) Physiological responses applied to only three vital signals

Psychophysiological research has hypothesised the connections between emotional responses and the concomitant variations on various body biological signals, however, not all of those hypotheses are generally agreed. Three biological signals were finally chosen in the proposed framework for emotion recognition due to the fact that they are the signals which most researchers agreed (Kreibig, 2010).

(d) Stationary measurement of vital signals instead of ambulatory

Ambulatory measurement of physiological responses is an ongoing and emerging discipline studying dedicated hardware, software and algorithm for a reliable and accurate monitoring of biological signals for non-stationary activities. This is way out of the scope for the current study to include ambulatory measurement of the physiological responses. Therefore, the present experiment only chose to apply stationary monitoring of the target biological signals.

(e) Emotion recognition through pattern matching without AI

The hypothesis of ANS specificity enables an emotion recognition using pattern matching for selected physiological signals (Levenson, 1992; Kreibig, 2010). Simple detection of signal trend was used in early stages of psychophysiological research, and machine learning algorithm based on computational intelligence has been adopted in recent research to increase the number of features and data samples which enhance the recognition accuracy. However, machine learning was not included in the current research because, first the study result was unlikely to benefit from using AI methodology to achieve our aim and, secondly the limited PhD time frame didn't allow the inclusion of an AI implementation on the proposed framework.

1.4.4 Ethical considerations

Ethical considerations for using human subjects in experiment has always been a critical step respecting the rights for each participant and protecting individual privacy (Orb, Eisenhauer and Wynaden, 2001; Shamoo, 2010). A set of rules were followed according to the regulations and policy defined by the ethical committee of the University of Reading[4], and a formal approval was obtained before proceeding the recruitment of participants for the experiment (approval number: SBS17-18 10). Appendix B contains the approval document.

1.5 Organisation

The next chapter summaries the literature review related to the current research and, based on the review, describes the proposal of the artificial sixth sense concept. The investigation on how IoT technologies help establish a common information exchange between machines and humans is presented in Chapter 3 which is a copy of the published paper for the first stage of the feasibility study. DUIs, a proposed natural interfacing method, is illustrated in Chapter 4 showing how the encoding and decoding of information contents may be a better HCI in ubiquitous computing for enhancing human senses as well as the simulation of the human sixth sense. This is the second stage of the feasibility study and is also the position paper published in the *Journal of Ambient Intelligence and Humanized Computing* of Springer for the current study confirming the research direction through a peer review process. Chapter 5 presents the details in designing the framework "*emotionWear*" for the present study showing the research method, the implementation of the emotion recognition platform and the conception & conduction of the experiment verifying the proposed hypothesis. The coverage of emotion recognition using common wearable biosensors and the *emotionWear* framework illustrated in the last chapter is presented in Chapter 6 validating

[4] http://www.reading.ac.uk/internal/academic-and-governance-services/research-ethics/

the hypothesis of the current research. According to the reviews and studies, Chapter 7 relays all findings from previous objectives and further discusses the results and observations related to the present research. Finally, conclusions and future works are summarised in Chapter 8.

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Chapter 2

Literature Review

The first aim of the present study proposed an artificial sixth sense concept which relied extensively on the literature review of previous multidisciplinary research from computing and networking technologies, to psychology and psychophysiology, and many other related academic areas. The study direction was confirmed by publishing a position paper (Hui and Sherratt, 2017) illustrating that human sixth sense could be predicted through emotional context awareness built on top of the IoT technologies. The literature research started from a survey of all related technologies for building the IoT concept and how contemporary technologies could be collected as the requirements for transforming the internetworking of sensors to the internetworking of people through all smart technologies (Hui, Sherratt and Díaz-Sánchez, 2017). The survey of IoT technologies was published in Elsevier's journal (see Chapter 3) and this paper acted as the technical background supporting the position paper published in Springer's journal (see Chapter 4). Based on the hypothesis of the position paper, an artificial sixth sense system was proposed and the background literature review for building an emotion recognition framework "*emotionWear*" and verifying the hypothesis is also described in this chapter.

Section 2.1 defines the human sixth sense and illustrates that it is a necessary ingredient in building a successful IoP. Section 2.2 depicts the related problems for building the IoP, and section 2.3 then proposes the IoS base on IoT technologies as possible solutions to solve the stated problems described in the previous sections. The artificial sixth sense concept is proposed in section 2.4. Finally, section 2.5 concludes the literature review and elaborates the hypothesis of the current research.

2.1 Sixth Sense

In addition to the five basic senses defined by Aristotle two thousand years ago, scientists in recent decades have also uncovered extra human senses such as the sense of balance through equilibrioception, the sense of heat through thermoception, the sense of pain through nociception and the sense of awareness of the position of body parts through proprioception (Wade, 2003; Macpherson, 2010). However, none of these relatively new senses is accepted by the academic community or the general public as the human sixth sense. Cultural issues may be the reason behind this exclusion since "*the sixth sense*" has always been associated with "*the ability to perceive the future*" based on the traditional folk concept (Macpherson, 2010; Hui and Sherratt, 2017). Alternatively, some research has treated this cultural sixth sense as related to trained and experiential judgements such as nursing and policing (A. F. Smith and Arfanis, 2013; Worrall, 2013). The present research presumes that both are similar concepts which perform estimation of an event based on past evidence and current facts, one is targeted for predicting future situations and the other focuses on retrospective investigation. The sixth sense throughout the whole thesis refers to the sense of perception forecast, especially the sense of predicting human emotional behaviours promoted by the perception of future conceived and remote emotional stimuli.

Human emotional responses, particularly physiological responses, are promoted by the human brain which orchestrates the different functional parts of the brain to innervate the visceral organs and muscles via the nervous and endocrine systems when the stimulation of perception is sufficiently strong (Cacioppo, Tassinary and Berntson, 2007; McCorry, 2007; Healey, 2014; Barrett, 2017). Specific physiological patterns driven by the ANS, or autonomic specificity, during dedicated emotion states have been observed as concomitant to the basic emotions proposed by Ekman and Levenson (Ekman, 1992; Ekman, 2016; Levenson, Ekman and Friesen, 1990). The recognition of emotion states can then be achieved by taking biomedical measurements of the various physiological signals such as heart rate, skin conductance, fingertip temperature and muscle contraction, and the combination of these signals is pattern matched for identifying the different discrete emotions (Wechsler and Jones, 1928; Mauss and Robinson, 2009; Kreibig, 2010; Landowska, 2014). Repeatability of physiological responses, autonomic specificity and coherence to the discrete emotions have always been the major criticism (Hollenstein and Lanteigne, 2014; Lang, 2014; Levenson, 2014), but a recent survey has shown that there is a higher proportion of scientists that agree on the concept of discrete emotions, especially the five emotion states: happiness, fear, anger, sadness and disgust (Ekman, 2016). Moreover, psychologists have discovered that individuals behave differently due to cultural (Matsumoto and Hwang, 2012; Jack et al., 2016), mental (P. Gilbert, 2015; Henry et al., 2016), physical (Critchley and Harrison, 2013; Shiota and Neufeld, 2014), contextual (Maren, Phan and Liberzon, 2013; Pierguidi et al., 2016) and experiential issues (Bergado, Lucas and Richter-Levin, 2011; Van Damme et al., 2016). The concepts of IRS, Situational Response Specificity (SRS) and the Conceptual Act Theory (CAT) further enhance the autonomic specificity to improve its consistency and coherence according to personal conceptualisation of the emotional situations (Hinz, 2000; Stemmler and Wacker, 2010; Hollenstein and Lanteigne, 2014; Gentsch, Grandjean and Scherer, 2014; Quigley and Barrett, 2014a). Therefore, the application of the same stimuli to different individuals may develop different perceptions and promote different discrete physiological responses according to individual emotion specificity (Stemmler and Wacker, 2010; Quigley and Barrett, 2014a; Hollenstein and Lanteigne, 2014; Evers et al., 2014).

If one can collect a database of daily life contextual stimuli with the corresponding physiological responses and applies it as ground-truth data to a supervised training algorithm, the forecasting of individual emotional responses may be possible for future stimuli based on dedicated statistical prediction models in machine learning. Excluding those related to paranormal activities, the prediction of human emotional behaviours is an emerging scientific research in recent years. Affective Forecasting, a term coined by D. T. Gilbert, Gill and Wilson (2002), investigated from a psychological perspective the human capacity for predicting future personal feeling and its focus is directed towards the individual bias that causes the common phenomenon of prediction errors (D. T. Gilbert, Gill and Wilson, 2002; Miloyan and Suddendorf, 2015). Thus, an external facility is a better choice for predicting future individual emotions. Emotion prediction normally relies on machine learning algorithm which recognises human emotions through statistical classification on training dataset (Rani et al., 2006; Stephens, Christie and Friedman, 2010; Kapoor, 2014; Kragel and LaBar, 2014). The ground-truth labelling of the training dataset is a significant challenge to effectively establishing the classification rules for an accurate prediction (Constantine and Hajj, 2102; Mariooryad and Busso, 2015; Ringeval et al., 2015; Yong, C. Wang and X. He, 2017). Computational Intelligence based on machine learning has become a well-established methodology for forecasting human emotions when:

a) the biomedical signals and the corresponding contextual or situational stimuli during emotional responses are combined to form features of a training dataset for machine learning;

b) the corresponding stimulated emotion states are used as the ground-truth labels for the dataset;

c) the ground-truth dataset is fed to a supervised training algorithm;

d) a specific classification method is chosen to get the best statistical prediction result.

Emotions not only help balance the internal systems of the human body through homeostasis (Cacioppo, Tassinary and Berntson, 2007; McCorry, 2007), but they also influence individual conscious and unconscious behaviours such as decision making, motivation, and social interaction (Damasio, Everitt and Bishop, 1996; Schwarz, 2000; Tsuchiya and Adolphs, 2007; Oatley and Johnson-Laird, 2014; R. Smith and Lane, 2016). Hence, the prediction of human emotions is crucial in understanding human intentions especially in HCI via AI (Hui, Sherratt and Díaz-Sánchez, 2017; Bartneck, Lyons and Saerbeck, 2017). Affective Computing intends to combine multidisciplinary knowledge such as computer science, psychology, physiology, biomedical engineering, neuroscience and many others for enabling computers to *have emotions* (Picard, 2001) thus computers can feel the users' responses and provide bespoke feedback mimicking natural human to human interactions (Picard, 1997; Picard, 2010). The areas applying affective computing, especially emotion prediction, have grown enormously where human mental health such as stress levels and mood can be continuously monitored (Greene, Thapliyal and Caban-Holt, 2016), user satisfaction on commercial services such as consumer product review can be objectively estimated (Patwardhan and Knapp, 2017), and human responses to safety such as improving driving attitude can be real-time assisted (Thirunavukkarasu, Abdi and Mohajer, 2016). However, the commercialisation of affective computing based on AI is still in its infancy even with a plethora of academic research in recent decades (Bartneck, Lyons and Saerbeck, 2017).

IoT is a promising application of ubiquitous computing where the interconnection of sensors has become a salient feature connecting electronically humans and machines together on one platform - the Internet (Hui, Sherratt and Díaz-Sánchez, 2017). IoT technologies provide the groundwork for building smart homes and smart cities which drive the IoT into the IoP. Decades of research has been conducted in manual driven console type interfaces interacting individual people with single computer gaining favourable results, however, the concurrent interactions between multiple users and multiple computers is still a technological challenge in IoP (Hui and Sherratt, 2017).

2.2 Internet of People

IoT, according to Ashton (2009), comes from an idea of automatic data capturing about the things in the physical world based on the application of sensing technology on the internet. The idea has recently evolved further to include contemporary technologies such as networking, software engineering, and materials science, where the interconnection on the internet expands from sensors to any network-enabled objects (Holler et al., 2014). Such objects have become so powerful due mainly to the miniaturisation of silicon electronics that enables the individual devices to gain various amounts of computing power (Hui, Sherratt and Díaz-Sánchez, 2017). These embedded computing devices, acting as the 'things' in IoT, are seamlessly and unnoticeably living with humans, thus a ubiquitous computing is weaving into the fabric of human daily life (Weiser, 1991). Additionally, IoT breaks the barrier between humans and computers by pushing the computers, or things, disappeared into the background, and this phenomena simultaneously creates new technological issues interacting humans with the disappeared HCI (Hui and Sherratt, 2017).

IoP is a logical extension of the current IoT by interacting computers with humans in a natural way. Weiser (1991) painted a beautiful and promising picture demonstrating how ubiquitous computing inextricably intertwined people with invisible computers. Over a quarter-century has passed and the current IoT architecture has fully implemented, if not outperformed, Weiser's blueprint although some interactive technologies are not yet commonly available to the general public (Hui, Sherratt and Díaz-Sánchez, 2017). M2M technologies play a major role enabling an effective communication between IoT's things, especially the application of semantic technology converting individual thing into entities of service abstractions (Barnaghi et al., 2012; Kiljander et al., 2014). The research on the interactions in Human-to-Machine (H2M) and Machine-to-Human (M2H) seems to fall behind the M2M technologies in seamlessly and simultaneously interacting IoT with huge number of users - the people, hence, a new barrier has inevitably put up especially for those computer novices. There is no formal definition of IoP so far but Miranda et al. (2015) have proposed a good starting point to describe the basis of IoP in four principles: *(i) be social; (ii) be personalised; (iii) be proactive; and (iv) be predictable*. From previous research, "be emotional" should also be involved as a major part of IoP either as the fifth principle or as a qualitative measure for the four proposed concepts. Without knowing the emotions through the recognition of users' affective states, or acting with emotions through the prediction of users' behaviours, a true Human-to-Human (H2H) interaction via H2M to M2M to M2H technologies may not be fully accomplished.

A straight forward approach for interacting invisible computing devices with DUIs is the diversion of the interfaces to alternative media such as the web services via web-browsers or social networking applications (Vilarinho et al., 2013; Dix, 2017). However, it is still not the final solution fulfilling the future demand of natural H2H interactions. Therefore a closer investigation into the interaction between things and people is required. H2M and M2H technologies are usually conceived as the same thing under the umbrella of HCI. The traditional console type interface using monitors, keyboards and mouses may not be suitable for contemporary computing especially when tangible interfaces are no longer an option for invisible miniaturised digital artefacts (Dix, 2017; Hui and Sherratt, 2017). The present research treats H2M and M2H as separate entities according to their structural and functional peculiarities in order to scrutinise the associated problems residing in the application of related HCI technologies. The hypothesis of DUI proposed from this research (Hui and Sherratt, 2017) reveals that the trend of DUI can be a de-facto standard for future invisible computing devices, since DUI represents a true NUI such that there is no requirement for learning when all interactions are as intuitive as the human nature (Lim, 2012).

M2H concerns the methodology of delivering information to people through stimulating the human sensory systems, such as visual, auditory, haptic, olfactory and gustatory senses. Contact and contactless stimulations are possible by contemporary DUI technologies providing users with multimedia content, tactile, taste and smell stimuli. A combination of multiple stimuli may enable a more accurate and rapid stimulation based on the multisensory integration capability of human beings (Beauchamp et al., 2004; Harrar, Harris and Spence, 2017; Hui and Sherratt, 2017). However, this is the content of information to be delivered to the target users instead of a traditional manual driven approach based on console type or artificial gesture type interfaces (Malizia and Bellucci, 2012). So the problem lies in choosing the right content for stimulating individual perceptions where different people may have uncommon or even opposite responses activated by the same stimulus due to IRS and SRS (Marwitz and Stemmler, 1998; Quigley and Barrett, 2014a).

H2M, on the other hand, focuses on an accurate collection of users' responses in ubiquitous computing via contact or contactless DUI technologies. AI algorithms are normally resided in the back-end of a H2M detection engine which deciphers the data coming from (i) body part movement, (ii) body sounds, (iii) body temperature, (iv) body odour, (v) body biosignals, or a combination of them (Hui and Sherratt, 2017). Users' behaviours or intentions are usually recognised by a statistical prediction algorithm based on machine learning, hence, ground-truth data from historical events must be properly collected and passed to the corresponding supervised training method in order to set up a classification rule for future prediction of personalised behaviours. The selection of features from past events as training dataset, and the ground-truth labelling of the data are typical problems that are difficult to address in machine learning (Constantine and Hajj, 2102).

Natural H2H interactions may be the ultimate target for effectively implementing both M2H and H2M technologies in IoP. Unlike the traditional manual driven User Interface (UI), H2H relies on content exchange which comprises of:

(a) Sensory stimulations which concern about the ways information contents are encoded and delivered to the target subjects.

(b) Cognitive appraisal of the stimuli and promote the concomitant responses as a reaction to the changing environment, and the detection and recognition of human responses is another concern.

(c) Behaviour prediction concerns the delivery of an affective interaction with the human users. For example, similar to human communication, a bespoke service or feedback should be delivered to acquaintance from historical interactions.

Figure 2.1 shows a concept of IoP based on IoT and IoS, section 2.3 will present the possible solutions to the above problems based on this concept.

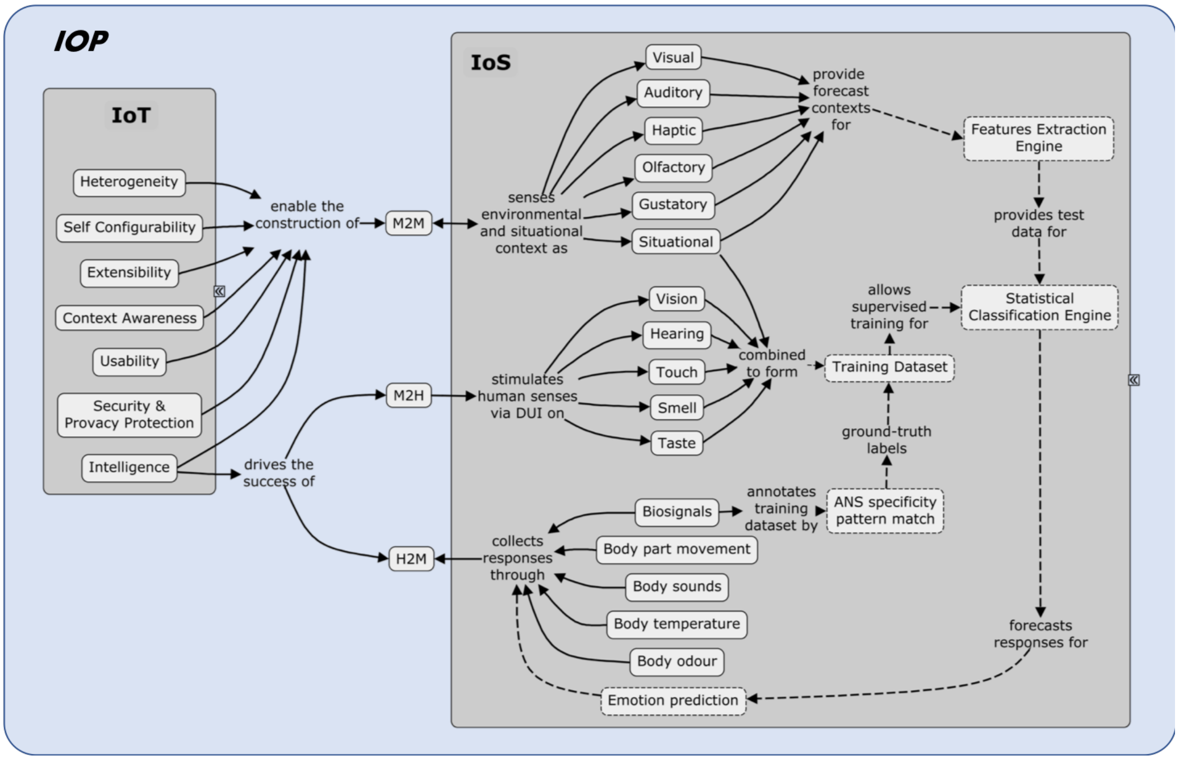

FIGURE 2.1: Internet of People Concept

2.3 Internet of Senses

The number of connected sensors on the IoT has accelerated dramatically since the various types of miniaturised smart sensors became an integral part of the smartphones. A recent prediction estimates that there are one trillion smart sensors by 2020 reported at the Trillion Sensors Submit[1]. The internetworking of sensors is part of the IoT empowering a huge sensory system spattered across the globe. If those smart sensors can be freely accessed, an IoT connected human may be able to extend individual sensory systems to this super sensory system sensing any remote environments across the planet. As a result, an enhancement of the human senses to super senses is easily achievable once a specific system based on novel computing algorithm and architecture is implemented to acquire and process the sensing data, for example, the detection of early warning of earthquakes, tsunami, flood and landslide in disaster management (Ray, Mukherjee and Shu, 2017).

When tangible interface is ineffective or unavailable for miniaturised computers, the concept of DUI provides a good alternative for natural intuitive HCI. A review of DUI in Chapter 4 presents the usage of disappeared UIs to collect user inputs from detection of

[1] http://theinstitute.ieee.org/technology-topics/internet-of-things/smarter-sensors

changes in body features (e.g. movements, sounds, temperature, odour, biosignals, etc.) and to deliver information contents through stimulation of the human sensory systems (e.g. vision, hearing, touch, smell, taste, etc.). There is a missing link bridging the computer inputs (or H2M), and the computer outputs (or M2H) that requires M2M technologies to intelligently decode the human intentions through emotional behaviours and deliver an affective stimuli as responses. This missing link is indicated in Figure 2.1 as dashed lines for all components invloved, and the understanding of human attention, cognition and emotion is required to realise its composition.

2.3.1 Emotion Perception

Since James (1884) asked the question "What is an emotion?" in 1884, scientists have been working on a formal definition of "Emotion" despite a plethora of unsuccessful attempts (Gendron, 2010; Deigh, 2014). The nature of emotions influences human daily behaviours, thus Plutchik has claimed that emotions "*is an essential part of who we are and how we survive*" (Plutchik, 2001). Emotion is closely linked to Cognition and Attention which drives the concomitant cognitive and autonomic activities such as making decisions and taking actions for surviving, or promoting perception for reaching homeostasis (Cacioppo, Tassinary and Berntson, 2007; Yiend, 2010; Wells and Matthews, 2014). Theoretical and empirical research shows that the human brain orchestrates the ANS and the endocrine systems which then innervate the visceral organs to produce autonomic specificity (Kreibig, 2010). The accuracy and repeatability of their results have been the major criticism for the advocates of basic discrete emotions (Ekman, 1992). Although previous research has indicated that emotional responses are not stimulated by a single stimulus, the CAT proposes a systematic explanation on emotion concordance and specificity according to a theoretical assumption on situated conceptualisation where an emotional response is constructed by the brain according to specific situations (Quigley and Barrett, 2014b). Environmental stimuli and internal sensations activate the limbic system which receives signals from afferent neurons through the thalamus acting as a sensor relay hub for human sensory receptions, moderates those responses by associating with the past experience through the hippocampus, and finally influences the hypothalamus which is the central commander for emotions interfacing the ANS and the endocrine systems. Once the hypothalamus is strongly influenced, it starts another biological process where electrical signals travel to the Sympathetic Nervous System (SNS) branch through the spinal cord and sympathetic chain then activate the famous “fight-or-flight" response, or calms down the human body and promotes the “rest-and-digest" behaviour through the cranial nerves relying on the Parasympathetic Nervous System (PSNS) branch (Cacioppo, Tassinary and Berntson, 2007; McCorry, 2007; Critchley and Harrison, 2013). The sensing of emotional responses can then be started by measuring the associated physiological variations, such as biological signal fluctuations (Stemmler and Wacker, 2010; Jerritta et al., 2011; Healey, 2014; Ramzan et al., 2016), facial and skeletal muscle contractions (Ekman, 1993; Levenson, Ekman and Friesen, 1990; Geangu et al., 2016; Jack et al., 2016), or prosodic cues in speech (Bisio et al., 2013; Yadav and Rao, 2015).

2.3.2 Emotion Measurement

Emotional responses can be captured by DUI technologies through remote sensing such as visual imaging and Radio Frequency (RF) leveraging which may easily be influenced by environmental issues, or on-body sensing such as wearable and implantable biosensors which allow a relatively accurate measurements of the corresponding physiological variables. There is still no evidence mapping specific areas of the brain to discrete emotions from latest neuroimaging research, thus the debate seems to be over on whether the perception of emotions is a “locationist approach” where discrete areas in the brain are responsible for individual basic emotions, or a “constructionist approach” where emotional responses are constructed by coordinating different functional areas of the brain (Kassam et al., 2013; Clark-Polner, Johnson and Barrett, 2017). However, the hypothesis of “Basic emotions” is still relevant in conceiving primary behavioural and physiological responses based on the findings of a recent survey (Ekman, 2016). Without considering how the brain orchestrates the responses, contemporary neuroanatomy and pyschophysiology show us a biological picture facilitating the emotion recognition using physiological measurements based on biomedical engineering. Research on autonomic specificity provides empirical evidence showing specific patterns of non-invasive biomedical measurements associated with the innervation and denervation of the visceral organs inside organisms not limited to humans but all vertebrate animals due to autonomic activities (Panksepp, 2011; Levenson, 2014). Motor programs activating the skeletal muscles of the face and certain parts of the body are also believed to be concomitant to the ANS during emotional responses and are normally treated as one of the contributors to the physiological specificity for emotions (Kret et al., 2013; Gothard, 2014; Shafir, Tsachor and Welch, 2016). Therefore DUI in IoT enables the sensing of emotional responses through the remote or wearable sensors detecting the physiological variations.

The current research focuses on using common wearable biosensors for measuring the emotional physiological responses due to their non-invasive nature and the convenience in acquiring the necessary hardware for proofing of concept. The wearable biosensors under the present study are:

- Photoplethysmography for heart rate variations
- Electrodermal Activity for skin conductance change
- Skin Temperature for small fluctuation of fingertip temperature
- Electromyogram for skeletal muscle contraction

(1) Photoplethysmography (PPG)

Emotions affect the heart rate through the two ANS branches which innervate the primary pacemaker cell: the sinoatrial node, causing an acceleration (through SNS) or deceleration (through PSNS) of the heart rate. Previous study has shown that the different signalling mechanisms using in the two ANS branches contribute to approximately 8 times faster deceleration of heart rate by PSNS than the acceleration by SNS (Appelhans, Appelhans and Luecken, 2006). Measuring the heart beat variation is conventionally done by Electrocardiogram (ECG) which shows an accurate Heart Rate (HR) through a multi-lead measurement. Photoplethysmography (PPG) is proved to provide relatively accurate HR using an indirect method with limitations on stationary measurements since motion artefacts drastically lower the accuracy (Charlot et al., 2009; Elgendi, 2012; Schäfer and Vagedes, 2013). Following the evidence from previous autonomic specificity research, only the HR feature of the cardiac variation is examined in the current study since this is proven by many researchers (Kreibig, 2010).

(2) Electrodermal Activity (EDA)

Emotions influence the SNS which innervates the eccrine sweat glands and initiates the secretion in a pulsatile manner with pulsations of 12–21 Hz (Boucsein, 2012). The reported latency for Electrodermal Activity (EDA) response varies from one to five seconds, and some research also indicates that a subliminal stimulation promotes a response in 100 to 200 milliseconds (Nava et al., 2016). The current research shows a quick EDA response which is activated almost immediately from the instance of elicitation for both still pictures and audiovisual stimuli (see Chapter 6 for details). It is believed that the response time is immediate according to previous empirical research and the configuration and condition of the present study. EDA measurement is also being used as stress detector[2] which shows significant responses during SNS activation. It is indicated from autonomic specificity (Kreibig, 2010) that EDA response increases at Happiness, Fear, Anger and Disgust, and decreases at Sadness. Thus, dedicated algorithms are needed to work with EDA detection to resolve the stressful situation whether it is "distress" which is harmful to health or "eustress" which is, on the contrary, beneficial.

(3) Skin Temperature (SKT)

Research on emotional skin temperature is relatively less active than other biomedical measurements such as heart rate and skin conductance, and the study on finger tip temperature related to emotions is even insignificant in recent years. Usually, the focus on studying emotion associated skin temperature is directed to facial temperature such as nasal tip, earlobes, and forehead (Salazar-López et al., 2015). Emotions induced vasoconstriction and vasodilatation that affect prominently on acral skin blood flow causing temperature variations was demonstrated as early as 1943 on finger tips (Kistler, Mariauzouls and Berlepsch, 1998). In order to limit the scope of research, Skin Temperature (SKT) in this study detects only the differences in finger tip temperature during emotional responses. Emotions mainly influence the SNS branch of ANS causing vasoconstriction and lower the temperature of the acral skin during emotional responses. Research shows that an effective demonstration of emotional fingertip temperature change occurs when the skin temperature is above 32°C before the stimulation, and the vasoconstriction lasts for 5 seconds (Kistler, Mariauzouls and

[2] http://affect.media.mit.edu/projectpages/iCalm/iCalm-2-Q.html

Berlepsch, 1998). This condition was met in the current study and the change in fingertip temperature dropped right after the elicitation as depicted in the response graphs during Fear, Sadness and Disgust. The change in skin temperature takes as long as 15 seconds thus detection needs to take readings for a period of time.

(4) Electromyogram (EMG)

Electromyogram (EMG) measures the level of muscle contraction (Tassinary, Cacioppo and Vanman, 2007). Since Ekman proposed the "Basic Emotions" together with the associated facial muscle activities during emotional responses (Ekman, 1992; Ekman, 1993; Levenson, Ekman and Friesen, 1990), facial expression has been a major research topic in measuring human emotions (Dimberg, Thunberg and Elmehed, 2000; Moody et al., 2007; Jack et al., 2016; Fernández-Dols and Russell, 2017) although the challenges on the universal nature of facial expression has never ended. Other than facial muscle, researchers have also hypothesised that emotional responses activate concomitant contractions on other skeletal muscles (Huis in 't Veld, Van Boxtel and Gelder, 2014; Huis In 't Veld, Van Boxtel and Gelder, 2014; Coombes, Cauraugh and Janelle, 2006). Since the detection of facial expression normally relies on visual imaging which requires good ambient lighting condition, the current study only focuses on surface EMG signals on biceps and triceps on the upper part of human arms to facilitate wearable measurements.

Recognition of emotions is the next step towards matching the physiological variables to the different discrete emotion states, such as happiness, fear, anger, sadness and disgust.

2.3.3 Emotion Recognition

Emotions can be recognised by mapping specific patterns of the measured biosignals based on autonomic specificity during an emotional perception (Ax, 1953; Levenson, 1992). Research on physiological measurements using individual biomedical sensors in recent years provides significant contributions to emotion recognition based on speech, facial expression or physiological responses (Picard, 1997; Picard and Healey, 1997; Cowie et al., 2001; Jerritta et al., 2011; Ramzan et al., 2016). Emotion arouses the ANS which activates the SNS and PSNS branches in order to promote physiological responses for balancing the different human biological systems and reaching homeostasis. Nevertheless, human emotion is not the only driving force behind the activation of the ANS. The automatic and self-regulatory functions of ANS are actually shared by many functional systems of the human body such as metabolism and startle reflex (Cacioppo, Tassinary and Berntson, 2007; McCorry, 2007; Mauss and Robinson, 2009). Examples include (1) ANS controls the cardiac functions which cause HR variations when SNS accelerates the heart beats and PSNS slows it down, but physical activities such as dynamic and static exercise can also increase the firing rate of the pacemaker cells causing a positive cardiac variations (Weippert et al., 2013), while people during sleeping will experience more PSNS activities causing a diminished heart rate (Acharya et al., 2006); (2) EDA, referring to the variations of electrical characteristics of the skin, is affected mainly by the SNS which activates the sweat glands causing secretion on the skin surface thus the electrical conductance during emotions is increased (Boucsein, 2012). Furthermore, a high skin conductance due to excessive sweat secretion is also driven by thermoregulation which relies on the autonomic functions causing sensible and insensible perspiration to maintain the body core temperature. People with hyperhidrosis especially primary palmar hyperhidrosis may get large amount of sweat secretion even with minor thermal or emotional activation, and patience with hypohidrosis may do the opposite that the dysfunctional sweat glands are not generating sweat in a normal way (Schestatsky, Callejas and Valls-Solé, 2011); (3) SKT variations reflect the fluctuations in skin blood flow which is the result of the vasoconstriction and vasodilatation of capillary vessels near the skin surface during emotional responses. ANS controls the vascular system to divert more blood to the specific visceral organs under different emotion states such that SKT becomes lower for certain skin areas with less skin blood flow. SKT then returns to normal when the requirement is not needed (Plutchik, 1956; Kistler, Mariauzouls and Berlepsch, 1998). Again, many factors will affect SKT other than the ANS influence, for examples, sex differences between male and female, ageing, metabolic rate, and medical history of the skin, etc. (Salazar-López et al., 2015; Fernández-Cuevas et al., 2015).

Emotion also activates the Somatic Nervous System (SoNS) which, similar to the ANS, influenced by the Central Nervous System (CNS) and coordinates patterns of voluntary skeletal muscle activities, such as facial expressions (Ekman, 1993; Müri, 2016) and other body movements and postures (Coombes, Cauraugh and Janelle, 2006; Coombes, Higgins et al., 2009; Shafir, Tsachor and Welch, 2016). EMG can be used to measure the level of muscle contraction due to emotional responses causing cholinergic activation of motor neurons through the SoNS (Tassinary, Cacioppo and Vanman, 2007; Gruebler and Suzuki, 2014). Emotion activated voluntary muscle contraction, both facial and body muscles, were treated as a concomitant of the ANS responses which trigger what Ekman described as motor programs associated with basic emotions (Ekman, 1992; Levenson, Ekman and Friesen, 1990). Recent research has found that emotional skeletal muscle contraction is an extremely complicated process which not only acts as emotion expression following ANS response concomitantly, it is also a means for social communication (Dimberg, Thunberg and Elmehed, 2000; Moody et al., 2007; Geangu et al., 2016), moderation of emotional perception (Kret et al., 2013; Gothard, 2014), and is hypothesised as a part of the newly conceived concept of Extended Emotions (Krueger, 2014; Carter, Gordon and Palermos, 2016). Cognitive muscle movement such as physical exercise, intentional emotion suppression, or even emotion deception can easily disturb EMG readings which affect emotion recognition accuracy especially during ambulatory measurements (Tassinary, Cacioppo and Vanman, 2007). Therefore, emotional responses that generate motor activities are often criticised as unreliable markers for accurate emotion recognitions (Beck, 2015).

Capturing mood (Sano et al., 2015; Zhu et al., 2016), stress (Mohan, Nagarajan and Das, 2016; Yoon, Sim and Cho, 2016), and affective or emotion states (Wu et al., 2015; Lee et al., 2017) have been the common goals for most of the recent emotion recognition research using psychophysiological wearables. However, many technical terms related to the different stages of emotions are not universally defined or academically agreed such as mood, feelings, stress, personality trait, emotional styles, etc. emotion state, an instance of an emotional perception with a corresponding response targeted to an object seem to be better defined since there have been extensive theoretical and empirical research from psychology, philosophy, psychophysiology, affective neuroscience and many other related disciplines (Sizer, 2006; Siemer, 2009). Results obtained from research on recognising and measuring mental stress are also debatable since bad kinds of stress (or distress) can be harmful to health but good kinds of stress (or eustress) promote positive feelings (Selye, 1976). Additionally, mental stress should be treated as a subset of emotion states since the same sensation to stimulation to perception process applies to both (Lazarus, 1993).

Autonomic specificity and concordance are the foundation for identifying and distinguishing different emotion states of target persons for emotion recognition, especially ambulatory emotion recognition, by matching the signatures or patterns of their biological responses using non-invasive wearable biosensors (Ax, 1953; James, 1884; Collet et al., 1997; Levenson, 2014). Emotion specificity based on physiological responses to emotional stimuli has been extensively researched with numerous empirical evidence amid constant criticism from opponents (Kreibig, 2010; Quigley and Barrett, 2014b; Saarimäki et al., 2016; Clark-Polner, Johnson and Barrett, 2017). Since the human brains orchestrate different physiological and behavioural responses according to the variations in individual emotional experiences and situations, the present research associates autonomic specificity with some basic emotions such as happiness, fear, anger, sadness and disgust, and has also acknowledged the concepts of IRS (Marwitz and Stemmler, 1998; Stemmler and Wacker, 2010; Duclot et al., 2016) as well as the CAT hypothesis (Barrett, 2014). This study will not rely on any argument between "constructed emotion" or "discrete emotion" approach, but is based on the previous theorical and empirical evidence from physiology that specific ANS activities will be promoted through the hypothalamus and affects the corresponding visceral organs once an emotion is perceived by the limbic system of the brain and there are also motor programs associated with some basic emotions proposed by Ekman (Ekman, 1992).

According to previous psychophysiological research (Kreibig, 2010), the hypothesis of ANS specificity for emotion recognition does not require the support from machine learning. A simple pattern matching using the biological signal trends is enough to recognise the basic emotion states of a human subject, however, machine learning can also apply to emotion recognition in order to increase the accuracy (Stephens, Christie and Friedman, 2010; Verma and Tiwary, 2014; Kragel and LaBar, 2014; Godin et al., 2015). On the other hand, emotion prediction will definitely be beneficial using AI and machine learning algorithms. Pattern matching and classifying can be done with single or multiple variables, and usually statistical pattern classification is chosen to be the method for emotion recognition and prediction (Rani et al., 2006; Bulteel et al., 2014; Saarimäki et al., 2016; C. He, Yao and Ye, 2017). Once a set of clean biosignals are collected and filtered, feature extraction is followed to get the required signals for analysis, for examples, magnitudes of the signals and their standard deviations, time and frequency domain derivatives especially on heart rate variability

(Camm et al., 1996; Koelstra et al., 2012). Ground-truth labelling of the datasets enables a supervised training algorithm to establish the required classifier for predicting future targets (Constantine and Hajj, 2102; Rani et al., 2006; Kapoor, 2014).

2.4 The Artificial Sixth Sense Framework

A framework for artificial sixth sense (figure 2.2) is proposed based on the above literature review and the previously conceived sixth sense concept from Chapter 1 section 1.1. Assumption has been made for human sixth sense to be the sense of emotional responses for future and remote stimuli (see section 2.1). IoT enables required technologies for M2M communications such that networked computers can talk and negotiate with each others in order to establish a smart environment (see Chapter 3). DUI empowers things to interact with humans through M2H and H2M technologies such that the sensing of the contexts that stimulate humans and the detection of human intentions and responses can be achieved (see Chapter 4 and section 2.2). Human emotions which affect individual behaviours may be recognised through a pattern matching algorithm based on the ANS specificity (see section 2.3). Recognised emotions together with the corresponding contexts can be archived and classified by supervised learning such that the emotional responses for remote or future contextual stimuli can be forecasted by statistical prediction based on AI methodologies (see section 2.3). Once a machine learning classifier is properly trained, remote or future stimuli including those that stimulate the human sensory systems, and the environmental context that the human subject is situated, can be fed to the classifier for target predictions.

The artificial sixth sense framework can be classified into four major functional blocks (refer to fig. 2.2):

(a) Emotion Recognition

This is the major functional block responsible for recognising individual human emotions. Once a set of biological signals for a particular physiological response is captured, the trend of each signal is compared with the ANS specificity hypothesised from previous researchers (Kreibig, 2010) and the results may point to a particular emotion state according to the magnitude of the signal trend. Various methodologies have been proposed for capturing the different type of physiological signals depending on the data collection situations such as stationary or ambulatory, and the major

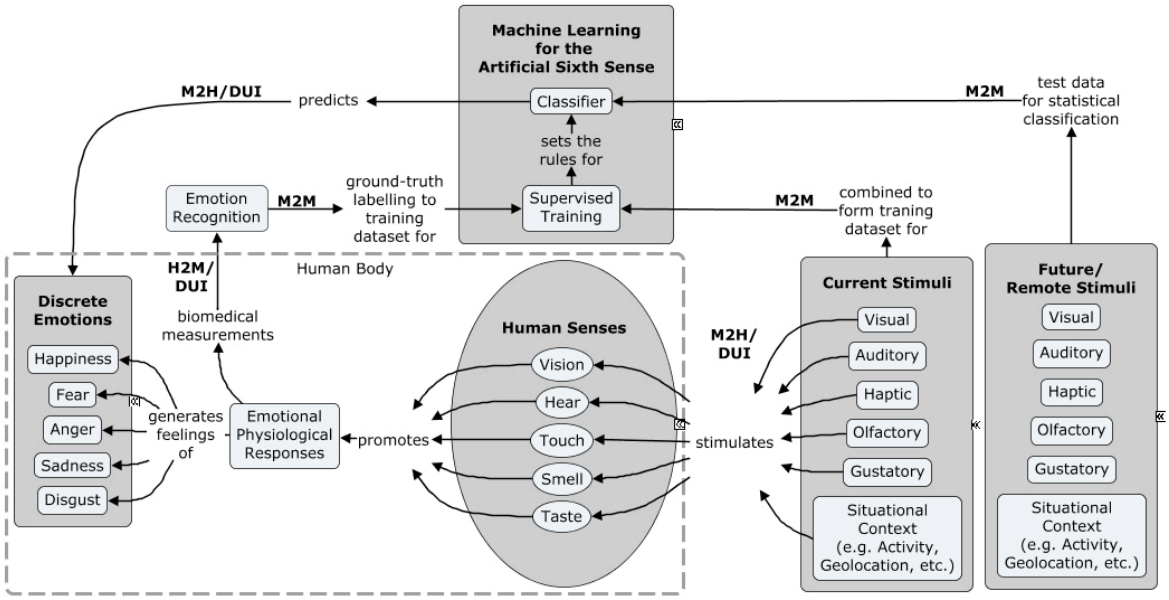

FIGURE 2.2: The Artificial Sixth Sense Framework

target is usually on increasing the measuring accuracy (Charlot et al., 2009; Jerritta et al., 2011; Healey, 2014). Recognition accuracy can also be enhanced through computational statistics such as machine learning especially when the number of variables for pattern matching is high (Stephens, Christie and Friedman, 2010; Kragel and LaBar, 2014; Verma and Tiwary, 2014; Godin et al., 2015), however, AI algorithm is not a necessary component in this functional block of emotion recognition.

(b) Current Stimuli Collection

The function of current stimuli collection captures all conditioned and unconditioned stimuli associated with the physiological responses promoted by the individual emotions. DUI technologies enable the collection of the contexts that affecting the human subject according to M2M communications through the IoT platform based on the ubiquitous computing concepts (Holler et al., 2014; Hui, Sherratt and Díaz-Sánchez, 2017; Hui and Sherratt, 2017).

(c) Future/Remote Stimuli Collection/Estimation

IoS and DUI together empower the capturing of context anywhere when Internet connection is reached. Presumably, the technologies for capturing immediate context are similar for remote context. However, AI may help classify the context according the their similarity so they can be used for emotion prediction. An IoT cloud computing platform makes the collection of remote context and data analysis or classification much easier to be implemented and accessed (Hui, Sherratt and Díaz-Sánchez, 2017).

(d) Machine learning for emotion prediction

Once the ground truth data for emotion recognition and the associated context (including the conditioned and unconditioned stimuli), a machine learning algorithm can train a dedicated classifier to do emotion prediction based on previous data. This is becoming a straight forward approach for contemporary AI for statistical prediction methodology (Kapoor, 2014; Rani et al., 2006).

There seems to be a missing technology for synchronising between emotional stimuli and the associated responses. Without knowing when exactly the response is promoted by the human brain, there is no way to identify what stimuli that actually cause the perception. Emotion recognition research normally captures physiological signals for a period of time after an emotional stimulation (Kreibig, 2010), but the verification of whether an emotional perception is stimulated or not, and the identification of the cause (or stimuli) for emotional perception is not obvious in previous literature. The clock synchronisation in a serial data communication bus such as UART (Universal Asynchronous Receiver and Transmitter), SPI (Serial Peripheral Interface), I2C (Inter-Integrated Circuit), is a mechanism to synchronise the data for a meaningful information reception in electronic engineering. Similarly, a “clock” signal may be an easy way to restrict the timing for capturing the physiological signals (i.e. the data) for further processing in emotion recognition. However, this “clock” appears to be missing in contemporary psychophysiology research.

Attention for emotional perception seems to be a method through the hypothesis of an OR activity (Bradley, 2009; Bradley, Keil and Lang, 2012) which indicates the process of analysing the contents of a stimulation due to an environmental change (Boucsein, 2012). An investigation of the relationship between the brain networks with the orienting of attention further strengthens the concept that an emotional perception promotes the concomitant physiological responses (Nieuwenhuis, De Geus and Aston-Jones, 2011; Posner, 2016). OR is an emerging research and its applications is still limited to the laboratory, particularly on audiovisual stimulation (Sokolov, 1990; C. A. Wang and Munoz, 2015; Barry et al., 2015). Despite OR is hypothesised as an indicator for promoting the emotional responses, it is not yet universally applicable to all types of emotional events. The current research would like to investigate if OR can help minimising the gap, therefore, our usage of OR applied to the areas that was proven by previous research as a proof of concept verifying the response-stimulus synchronisation hypothesis.

2.5 Conclusion

Literature review for this research has been done on three major areas of knowledge: IoT technologies, DUI for disappeared computers in ubiquitous computing, and human emotions from emotional stimulation, perception, promotion to recognition. Theoretical and empirical research has turned concepts, and hypotheses into theories and practice in many areas. An artificial sixth sense concept proposed in Chapter 1 has turned into a design framework based on past literature, however, the transformation of concept into practical development is not yet available. A hypothesis of missing technology on synchronisation between emotional stimuli and the corresponding responses is proposed and this is the main aim of the current study to validate the proposed hypothesis (see Chapter 1 section 1.2).

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Chapter 3

Major Requirements for building Smart Homes in Smart Cities based on Internet of Things Technologies

This chapter is a literature review on IoT technologies which empower smart interactions between ubiquitous and pervasive computing devices based on machine to machine communication. A taxonomy of technologies according to the different requirements for building a platform from the internetworking of sensors to the internetworking of people is presented, and it is the groundwork for designing an experimental framework for proofing the hypothesis of the current study. The survey also provides the technical support for an intuitive human to machine communication which is the background for a position paper presented in Chapter 4.

A version of this chapter has been published in the Elsevier Journal of Future Generation Computer Systems and the content of the current chapter is an expansion and enhancement of the journal paper with additional details to further clarify related concepts, provide explanation on the review process, and establish coherence and flow between chapters allowing the content to be part of the whole thesis.

> *Hui, T.K.L., Sherratt, R.S. and Díaz-Sánchez, D. 'Major requirements for building Smart Homes in Smart Cities based on Internet of Things technologies'. Future Generation Computer Systems 76. Supplement C (2017), pp 358-369, DOI: 10.1016/j.future.2016.10.026.*

The recent boom in the IoT will turn Smart City (SC) and Smart Home (SH) from hype to reality. SH is the major building block for SC and have long been a dream for decades, hobbyists in the late 1970s made Home Automation (HA) possible when Personal Computers (PCs) started invading home spaces. While SH can share most of the IoT technologies, there are unique characteristics that make SH special. From the result of a recent research survey on SH and IoT technologies, this chapter defines the major requirements for building SH. Seven unique requirement recommendations are defined and classified according to the specific quality of the SH building blocks.

3.1 Introduction

The term "Internet of Things" first appeared in 1999 when Ashton (2009) presented a report on Radio Frequency IDentification (RFID) to Procter and Gamble. The idea of automatic data collection using RFID and sensing technology, together with the continuous development on WSNs, M2M architectures, AI and semantic technologies have enabled IoT to blossom. Cisco has predicted that 50 billions of "Things" will be connected to the Internet by 2020, likely to be 6.58 times more than the estimated world population (D. Evans, 2011). Holler et al. (2014) pointed out that the major reason for IoT to take off was the need to enable technologies at the right cost.

IoT is considered as an extension of the existing Internet where H2H interaction has dominated the daily network communication. Familiar H2H examples are text messaging, voice and video conferencing and social networking. H2M interaction has become another important part of Internet communication when machines get smarter with AI. A smart machine, or intelligent computer server, can tailor make content for a dynamic web page and present it to a particular user according to his/her browsing history. Miniaturisation of electronic components according to Moore's law enables networked computers to be embedded into anything we want. Thus "Things" are becoming computerised, smart, and connected to the Internet as well. Computers will be everywhere, network connected, and invisibly living with humans: a situation described by Weiser (1991) as ubiquitous computing over two decades ago. IoT is a concept to get Things connected to the Internet, and Thing-to-Thing or M2M interaction is the core IoT technology. Global scale IoT applications have been found in many areas from domestic to industry and from national to international.

Cyber Physical Systems (CPS) adopting IoT technologies seamlessly integrate physical components with cyber space through contemporary computing and networking technologies. The real-time operation in the physical world dictates the difference of CPS from today's computing and networking abstraction (E. A. Lee, 2008). Typical CPS applications are SH and ambient intelligence where the monitoring, controlling and automating functions are accomplished through connected sensors and actuators. Tele-care services support elderly and disabled people to connect to health care monitoring services provided by medical institutions from a distance. Telematics makes driverless vehicles commuting in the cities possible by feeding wireless real-time road traffic information constantly to the built-in car navigation systems.

Smart grid focuses mainly on energy saving for homes and businesses based on the power grid to collect usage data from appliances. IoT technologies support the algorithms for balancing the power from the power plant and the in-house power sources, e.g. solar panels, and give the users a better decision about energy consumption (Guinard, 2011).

Industry has recently embraced IoT technologies to boost productivity. "Industrie 4.0" is now a popular term in Germany. It describes a vision of the 4th industrial revolution following the three previous generations: mechanisation (Industrie 1.0), electrification (Industrie 2.0) and digitialisation (Industrie 3.0) (Drath and Horch, 2014). At the same time, General Electric (GE) has proposed similar vision for US industry by redefining the term "Industrial Internet" which integrates the three elements: intelligent machines, advanced analytics and people at work to increase the manufacturing output (P. C. Evans and Annunziata, 2012).

SC applies the technologies into a much wider scale by connecting people in a city to all "smart technologies" mentioned above in order to deliver real time information for selected users with correct details at the right time. Figure 3.1 shows a typical integration of smart technologies in a SC architecture.

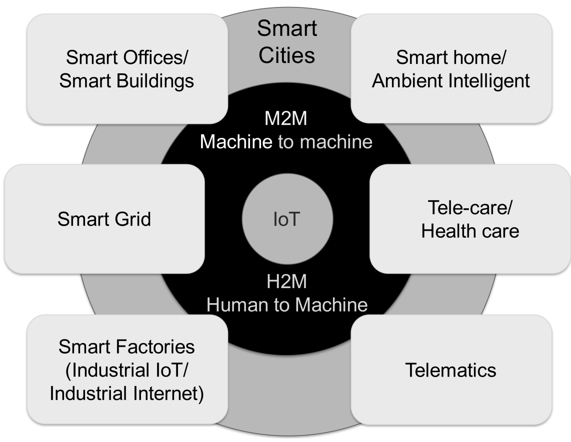

FIGURE 3.1: Typical Architecture of a Smart City

This chapter discusses the latest SH research based on IoT technologies with the objective to classify them into a list of major requirement recommendations for building SH systems. Section 3.2 describes the latest sensor network technologies and proceeds to list the seven major requirements to build SH systems defined from this work. The challenges we have seen in meeting this requirements are discussed in section 3.4. Finally a conclusion with future work is presented in section 3.5.

3.2 Smart Homes and Smart Cities

SH is the basic building block for SC, and the establishment of SC is a core enabler for the rapid global urbanisation. By 2050, 66% of the world population will be living in urban areas while the number of "mega-cities" with 10 millions inhabitants or more is expanding in the same pace[1]. A people-centric design approach is adopted in building SC in order to share resources effectively and intelligently, however, provision of tailor-made services to individual inhabitants is difficult without collecting and learning personal behaviour in public spaces such as smart offices, smart factories, and public transport. SH is the best venue assisting SC to gain personal data when privacy protection is properly implemented.

SH and HA are used interchangeably in the thesis and they refer to the applications of IoT technologies in the home environment. A high degree of heterogeneity makes the connections difficult due to many interfacing technologies available in the market. Things to be connected at home can be low-resource devices such as self-powered light-switches using energy harvesting as power source, or battery operated temperature sensors which wake up every ten minutes, or even fully equipped multi-core desktop PCs running 24-hour per day. Repetitiveness of control processes may vary from 100 times per day down to once per year.

The story of SH began in the late 1960s when computer amateurs started installing computers at home, and one of the famous home computers at that moment called ECHO-IV was installed by Sutherland for family bookkeeping, inventory taking, as well as house temperature control (Gotkin, 2014). When PCs appeared in the mass-market in the late 1970s (Abbate, 1999), on-site controlling and automating of home appliances became Do-It-Yourself (DIY) projects by hobbyists. Remote control was achieved by decoding Dual Tone Multi Frequency (DTMF) signals through telephone lines when a domestic Internet service was not

[1] http://www.un.org/en/development/desa/news/population/world-urbanization-prospects-2014.html

yet generally available (Koyuncu, 1995). Research in SH has been progressing but the real adoption is still very low. Greichen (1992) described in 1992 the emergence of SH market was "*just around the corner*" after a decade of research and implementation. Nowadays, after passing another decade from Greichen's work, we have not seen significant SH adoption yet and the high cost, difficult installation and unfriendly operations are still the main obstacles transforming the hype to reality.

3.2.1 Sensor Networks for Smart Homes

The networking of Things such as sensors and actuators is the basic enabler for M2M connectivity. Things can be connected using wired or wireless technologies depending on the home environment. For a wireless connection, short range and long range radio links provide two different communication paradigms to fit for different system architectures.

Wired sensor networks connect Things with fixed wires which are not convenient in terms of installation and extensibility for future upgrade. Wiring may be required to form a home network for transmission of control data, and the network is usually in the form of "bus" structure such as CEBus, KNX[2] and LonWorks. Data transmission over power lines eliminates the needs for running separate physical wires and is good for the retrofit market, Home Plug, Insteon and X10 are typical examples in this category. X10 has been popular in the DIY market since 1975 when Pico Electronics invented the protocol using power lines as data transmission medium (Withanage et al., 2014). This technology has become a de-facto standard in SH for many years due to its ease-of-use, easy-of-install and easy-of-upgrade by plugging into any power outlet to form the SH net. The notoriously unstable performance due to power line interference prevents X10 to prevail in the SH market, however the high cost-performance-ratio still keeps X10 products in production. Ethernet, except the usage in setting up Local Area Network (LAN) for communication between computers, is also a good candidate for SH connectivity requiring high bandwidth such as high-end audio and video streaming at home. Many wired networks also provide wireless options to cope with the restriction on physical wiring, e.g. Wireless X10 and Wireless KNX.

Bus based SH technologies such as KNX and LonWorks have not penetrated in the home market except for building management and luxury properties due to their elevated cost but KNX, for instance, is still one of the best choices due to stability and reliability for SH.

[2] http://www.knx.org

The major goals of KNX have been detaching the transmission from the control logic and enabling the compatibility among function modules from different manufacturers irrespectively of the underlying transmission technology. KNX relies on the OSI protocol stack and use their own addressing space based on device addresses to interact with a single device and group addresses for joint operation of similar devices. In KNX systems, the function module is governed by a small microprocessor that implements the upper layers and the entire module is plugged into bus coupler that implements lower layers according to the desired transmission technology that can be low power buses, power line, RF and infrared. The number of devices is limited by the transmission technology and the length of the wires. While IoT for SH opens a number of new possibilities, these buses are interesting especially for HVAC (Heating, Ventilation and Air Conditioning) systems and critical infrastructures due to their isolation and reliability. Among the requirements for SH, IoT should provide equivalent security to become an alternative in the context of critical equipment management inside a home environment. Moreover, device interworking, guaranteed in KNX, is still one of the major problems in IoT due to the lack of standards.

A proliferation of ubiquitous WSN protocols has enabled WSNs to dominate the M2M connectivity technology in SH. Low cost, low power, self configurable and expandability are major design criterion for WSNs. Short range radio fits the low cost and low power requirements while mesh networking architectures provide the network nodes to be self-configured dynamically and offer easy expansion. Zigbee[3] and Z-Wave[4] are the most common home control WSN protocols that provide low cost, low power mesh network connectivity. Bluetooth[5] has long been positioned as a personal area network connecting up to seven surrounding devices not exceeding a maximum of 100 meters (for class 1). With the newly introduction of BLE 4.1, Bluetooth mesh networking (or Bluetooth Mesh) is possible now to compete with other mesh WSN technologies.

Most wired and short range WSNs require connection hubs or gateways to convert and route internal network data in and out to the Internet. A long range WSN becomes necessary for applications requiring direct wireless connection to the Internet. Cellular networks (e.g. EDGE, 3G, LTE, NBIoT, LTE-M, etc.) provide Internet connectivity for Internet Protocol

[3] http://www.zigbee.org
[4] http://www.z-wave.com
[5] http://www.bluetooth.org

(IP)-enabled devices, but the connection cost is relatively high. A combination of short-range WSNs and the cellular network is sometimes referred as a capillary network which enjoys a complete wireless connectivity for home devices using a cellular connected gateway to exchange WSN's data to the Internet through cellular radio (Sachs, 2014). New Low Power Wide Area Network (LPWAN) standards from Weightless[6] using TV white spaces, Sigfox[7] and LoRaWAN[8] using sub-GHz carrier frequencies are proposed as wireless data links enabling cheaper alternatives for long range M2M connectivity at home (Bedogni et al., 2013; Webb, 2013; Barker and Hammoudeh, 2017).

6LoWPAN[9], also based on IEEE 802.15.4 like Zigbee and WirelessHart, enables direct IPv6-connectivity to the Internet for resource-limited nodes in WSNs, and its open standard nature supported by IETF (Internet Engineering Task Force) will hopefully make it stand out from the competition. However, different proprietary standards for WSNs are being proposed at the same time from the industry such as WEAVE from Google and HomeKit from Apple, it may take a long time to converge to a globally acceptable protocol standard for SH and IoT.

3.2.2 Major requirements for building smart home

High degree of heterogeneity, low repetitiveness, polarisation of user experience, demands of security and privacy protection, are all typical and critical characteristics of SHs. Human-in-the-loop demand is higher than any other IoT applications since humans are the ultimate owners of all Things in the home space. The complexity escalates when there are multiple owners in a single home space where multiple but different rules must be applied at the same time, in the same place, for the same Things. Yamazaki (2006) argued that total automation as the goal of SH technologies was a mistake preventing SH to prevail in the 1970s. Intelligence is becoming a basic ingredient to get automation smarter in SH and IoT technologies.

This chapter summarises the major requirements from previous literature review focusing on SH and IoT. Although SH has been researched and implemented for decades, adoption of SH is still at its infancy. This chapter defines the major requirements and proposes

[6] http://www.weightless.org
[7] https://www.sigfox.com/en
[8] https://lora-alliance.org/about-lorawan
[9] https://tools.ietf.org/wg/6lowpan/

the essential elements for building SH with IoT technologies. While it is believed that more requirements will be revealed in the future when SH becomes more mature, the major requirements derived from this review are found to be:

1. Heterogeneity
2. Self configurable
3. Extensibility
4. Context Awareness
5. Usability
6. Security and Privacy Protection
7. Intelligence

The following sections now describe each requirement in detail.

(1) Heterogeneity

Heterogeneity is the ability to let different types of connected Things exchange information in a given network. Things are typically electronic devices embedded with network-connected computers, they may have different processing power, different input-output facilities, different scale of resources, different connectivity technologies, and different communication protocols.

Things exchange information easily when they connect with the same connectivity technology inside a given wired or wireless network. When Things are not IP-enabled devices, the connection to the Internet is done through a gateway to translate the non-IP to IP connectivity. The level of heterogeneity increases when two or more networks with different technologies are required to work together. The connection gateway architecture provides a platform so heterogeneous Things can talk to each other in a combined network.

Perumal et al. (2008) defined three interoperability levels for heterogeneous systems: (1) basic connectivity interoperability concerns more on the physical connections of devices; (2) network interoperability describes the data communication management, and (3) syntactic interoperability refers mainly on the application level. The authors verified the concept of the home system with a home gateway running Simple Object Access Protocol (SOAP) to link up all heterogeneous sub-systems. To simplify the structure, they only used Ethernet to connect all heterogeneous devices running the Transmission Control Protocol (TCP) protocol.

Server Centralised Architecture (SCA) was described by Li and G. Xu (2008) as the approach to connect devices in the home space using a home gateway. They proposed that appliances can be divided into device and service layers in order to identify devices as services instead of individual functional interfaces. The authors further proposed a Server Oriented Architecture (SOA) to increase the degree of heterogeneity for some servers in terms of scalability, interoperability and reliability. A network of physical devices becomes a network of services using this approach. Figure 3.2 shows a typical heterogeneous network for the home.

Ontologies have been widely proposed as a vehicle to reduce the impact of heterogeneity in IoT (Hachem, Teixeira and Issarny, 2011). These approaches deal with the heterogeneity of IoT components and also the unknown nature of the network topology (and their dynamic nature) by modelling a set of ontologies that describe device functionalities. Complementary, others, as (Rubio-Drosdov et al., 2015), model ontologies for describing the communication interface at application level. Several efforts, as Guinard, Trifa and Wilde, 2010 focus on orchestrating things around existing ontologies. Even though ontologies are valuable tools for describing things, functions, services and interfaces, and reducing the impact of the heterogeneity, their processing involves a huge resource consumption. The use of ontologies could be embraceable in practice by offloading their processing to a cloud or a home gateway.

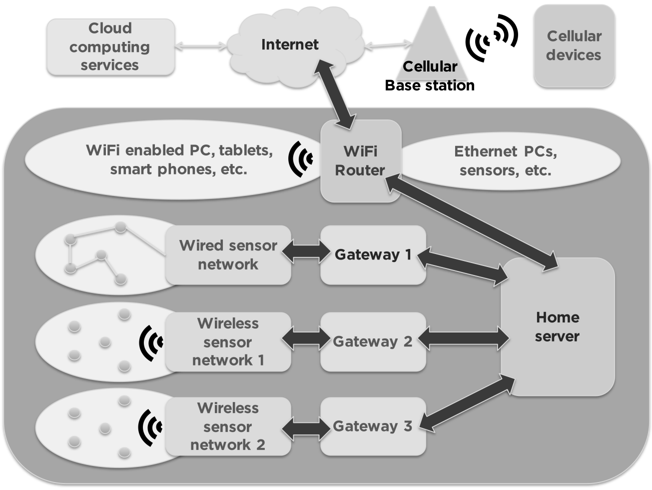

FIGURE 3.2: Typical Heterogeneous Home Network

A software framework accommodating all the related services in a home network becomes a convenient and efficient way to establish a network of Things. Open Standard Gateway initiative (OSGi)[10] started from set top box design provides an open specification based on SOA for setting up a framework using Java technology. Middleware runs

[10] http://www.osgi.org

on top of the framework to exchange information between individual service. Ready made middleware can be found that works seamlessly with other user applications in the same framework. A typical example is a service discovery application, e.g. SLP (Service Location Protocol) or UPnP (Universal Plug and Play), which is useful to locate services in a heterogeneous network. Maternaghan and Turner (2011) proposed a tele-care system based on OSGi framework, they also turned the research project into a product called Homer which linked up components and services in an OSGi enabled home server. Homer provided control and automation algorithms to all connected components through its own application programming interface which may be an obstacle for general adoption by various manufacturers.

A combination of middlewares and gateways has been dominating the home server architecture for recent years. An obvious off-loading of the home server is happening with the proliferation of cloud computing services and the popularity of high speed home broadband. Simple gateways performing protocol conversion is enough to connect Things in WSNs to the Internet through the cloud. Dealing with complex compound services within the home environment and the cloud has triggered the development of scalable technologies that transfer partially the data centre cloud technology to the home environment or federations of users equipment. Some works such as Díaz-Sánchez, Almenárez, Marin et al. (2011), M. Tan and Su (2011) and Van-Dang and Y. Kim (2014) proposed middleware for set-top boxes and gateways for classifying, searching, and delivering media inside home network and across the cloud that interoperates with several home protocols. Others went a step beyond providing also frameworks for distributing applications (Díaz-Sánchez, Almenárez, Marín et al., 2014) or accessing secure home services from remote locations transparently without breaking home protocols. All these movements have triggered the concept of fog computing (Bonomi et al., 2012; Stojmenovic, 2014) that basically defines a new set of devices, called fog devices, between the device and the cloud, that can absorb partially the load that would be otherwise delivered to the cloud leveraging resources that would be misused and reducing the exposure of private data (see Figure 3.3).

Services from many cloud computing suppliers provide connection with XaaS (Everything As A Service) for remote monitoring, controlling and automating Things in the SH sector. Soliman et al. (2013) demonstrated a home network to the cloud based on SaaS (Software As A Service) and PaaS (Platform As A Service). Zigbee devices were connected to the cloud though a simple Arduino-embedded gateway, and all management and security services were provided in the cloud through common web services. Heterogeneity is achieved with the plethora of contemporary home management services from the cloud computing suppliers.

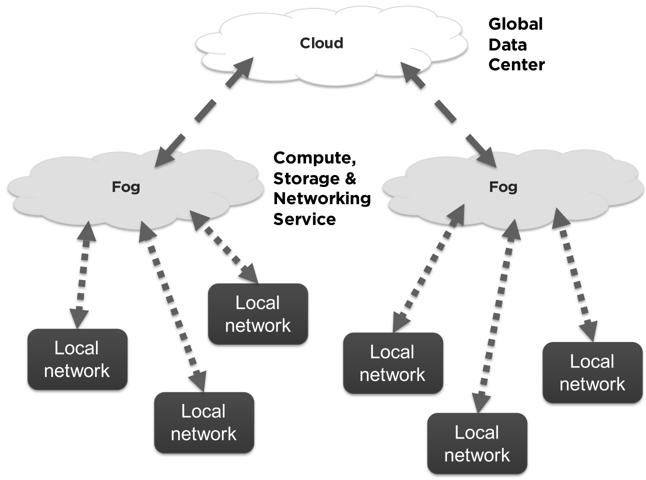

FIGURE 3.3: Typical Fog computing system architecture

Applications in IoT generate huge amount of information worth to be processed. To facilitate interaction with the cloud, manufactures are developing small general purpose boards with a built-in operating system, libraries and the software development kit for connecting things to their cloud services, providing so a customizable solution for IoT in a single bundle. Despite off-loading to the cloud complements IoT local applications with several other services, it also introduces a major problems as data lock-in. IoT frameworks for SH should support alternatives to current closed manufacturers' clouds like actor or data flow models in which applications can be distributed to and instantiated in several different locations and orchestrated in a simple way using asynchronous messaging.

Aligned with the latter, it would be necessary to connect manufacturers and developers to businesses and consumers in a standardized way as proposed by the COMPOSE project in their market place for the IoT [11].

(2) Self Configurable

Self-configurable refers to the capability to add and remove Things in SH networks automatically through altering the context of the Things or the network topology. Things in SH are sometimes non-permanent residents, such as consumables (e.g. a light bulb, an ink cartridge, etc.), or movables (e.g. a mobile heater, a trolley, etc.), or wearables (e.g. a smart

[11] http://www.compose-project.eu/

watch, a heat rate monitor, etc.) and they may come and go from time to time. The re-gistration and re-registration processes should be done quietly and autonomously without user intervention. Self-installation for brand new Things in SH contributes to another measurement for this requirement. New technologies from the market or new requirements from the home owners usually gain new members to the existing SH network, an easy installation helps the market grow. First time installation of SH systems normally requires professionals. Easy setup process or auto-setup will be the ultimate goal for non-technical users when SH technology becomes more mature (Englert et al., 2013; Valladares et al., 2013).

Existing mesh WSNs already provide self-configuration algorithm to recover the network operation when there are defective nodes or broken paths blocking the data flow in a network (Dressler, 2008; Stankovic, 2008; Bein, 2009). Hwang (2009) pointed out that the simple self-configuration and self-healing mechanism provided by Zigbee specification is too slow. The low power nature of Zigbee network prevents the nodes from frequent wake up and the detection of a beacon lost will be slow to confirm the loss of synchronisation. An orphan scan initiated by the loss confirmation will then renew and recover the routing according to a preset response time. An enhanced method was proposed by Hwang to speed up the self-configuration and self-healing processes, as well as to improve the orphan propagation problem from the user application layer.

There are other popular mesh WSN technologies available in the market supporting self-configuration and self-healing mechanism such as Z-Wave, WirelessHart[12], etc. An interesting alternative is BLE (or Bluetooth Smart) which also supports mesh networking with a scatternet topology. Scatternet combines many piconets and the master of each piconet becomes slave of adjacent piconet, thus this combination turns many single hop personal area networks into multi-hop mesh network. Scatternet was defined together with piconet as the network topologies in early versions of Bluetooth specification and some research has already proposed methods implementing mesh networks based on scatternet specification (Cuomo, Melodia and Akyildiz, 2004). ABI Research's forecast of 10 billions Bluetooth-enabled devices in the market by 2018 puts Bluetooth back under the spotlight (K. H. Chang, 2014). Bluetooth SIG has recently setup the Bluetooth Smart Mesh Working Group to promote the technology for IoT.

There is still very little research on auto-setup for SH up to now, only methods on easy

[12] http://en.hartcomm.org

configuration or easy setup are found. An earlier attempt by Leeb et al. (1996) back in 1996 presented a configuration tool called Homenet for configuring home appliances using a GUI on a computer console. Their idea relied on the fact that users usually added appliances one by one so users became the installer all the time. Each appliance was represented as a list of functions and users configured the appliances by combining functions of different appliances to form an object. The procedure looks intuitive and easy to operate but the prerequisite is the provision of the list of functions from appliance manufacturers.

In a different approach, S. Y. Chen and Y. F. Chang (2010) promoted expert assistance from installers and designers through cloud services. An interaction based on cloud computing links up users, designers, manufacturers and installers together to complete a tailor-made SH system. SaaS combines different applications in cloud computing and achieves the goal from drafting user requirements, to setting proposals, to selecting products all in the shared Computer Aided Design (CAD) applications. Users are heavily involved at the beginning to define the requirements and all technical details are hidden. When the platform grows with more designers and manufactures, the burden of users as installers can be offloaded to selected experts.

Other approaches, more related with WSN but applicable to the IoT SH, have developed SensorML as a lightweight markup language to describe sensors and actuators in a very simple way (Aloisio et al., 2006) [13]. SensorML does not provide the richness of ontologies when it comes to define Things in general but it may have an important role to play in the context of IoT for SH since many device manufacturers may find the language expressive enough for small or single purpose sensors and actuators. Similar emerging concepts based on ontology, semantics or feature models are becoming popular in SH research and will further improve the self configurable quality (J. Xu et al., 2009; Kao and Yuan, 2012; Cetina et al., 2009).

(3) Extensibility

Extensibility is the capability of a SH system to extend the functions or configurations of the connected Things, the scale of the network, and the adoption of new technologies.

WSN is always a better choice over wired network for SH networking in terms of devices upgradability and network scalability. Data over power-lines improves the extensibility in

[13] http://www.opengeospatial.org/standards/sensorml

certain extent but the bandwidth is normally not enough for upgrading the functions of connected devices. Over-the-air (OTA) software update has long been a feature for many WSN technologies, including Zigbee, Z-Wave, 6LoWPAN, BLE and many other WSN protocols. Brown and Sreenan (2013) studied the different techniques for software updating in WSNs, and the possible problems affecting the reliability of code transfer mechanism. Autonomic software and configuration upgrade is a critical feature for WSNs as a post-deployment strategy, deficiency in the current technology in terms of updating management on error handling, feedback and configuration should reveal more research in the coming future.

Extending the scale of the network is also a built-in feature for most of the mesh network WSN architectures. Adding or removing a device in a mesh network activates the reset of a routing table which requires intelligent algorithms to avoid a slow response due to the infrequent wake up time for power-constrained network nodes as we have discussed in section 3.2.2 (Akbal-Delibas, Boonma and Suzuki, 2009; Allen, Forshaw and Thomas, 2017).

Good examples of modular design in a form of service oriented middleware running on a dedicated server or gateway were demonstrated by Álamo and Wong (2008), H. Y. Huang, Teng and Chung (2009) and Götze, Kattanek and Peukert (2012). All modules were upgradable and new modules could be added as long as they used the same interfacing standard. The authors reviewed the difficulty when the same modules were working loosely without a common standard mechanism. An alternative common platform is available from the recent boom on cloud computing which provides an API for users to configure the services through a simple web service protocol using web browsers (Ye and J. Huang, 2011; Igarashi et al., 2015).

As mentioned before, the actor model can complement SH (Díaz-Sánchez, Sherratt et al., 2015) with pretty good extensibility. The actor model is a well-known mathematical model of concurrent large scale computation. Actors are the universal primitives of computation being actors small single threaded applications with a mailbox and some state. The actor behaviour is controlled by the internal state and the messages received. Since actors run isolated from each other it can help controlling the resources it consumes whereas enable the deployment of a number of other new functionalities to an existing device just adding new actors remotely. Software driven approach has proven to be flexible and extensible through dynamic configuration of system resources such as multiple agents or duplication of controlling or sensing targets (C. Lu, Wu and L. Fu, 2011).

(4) Context Awareness

Context awareness concerns the capability to detect and react when a Thing itself is changed (e.g. it is moved to a different location, or its property is altered, etc), or the surrounding environment gets changed (e.g. new Things or services are added or removed from the surrounding, etc.).

The concept of context-aware computing was proposed by Schilit et al. in 1994. The authors claimed that the three important aspects of context were: "*where you are, who you are with, and what resources are nearby*" (Schilit, Adams and Want, 1994). Proliferation of mobile computers created the new mobile distributed computing paradigm when mobile met with stationary computing devices. Context detection of the mobile device enables the provision of timely, accurate and relevant services in ubiquitous computing. A simple IF-THEN rule activates proper actions when context is changed, but a more advanced algorithm, or even intelligence is needed when there are multiple context changes in the same environment. The major problem encountered by the authors was the provision of a timely and accurate reaction on contextual information. Hong, Suh and S. J. Kim (2009) provides a groundwork for practical implementation of context-aware systems by classifying necessary components into a five-layer architecture through a literature survey of 237 research articles.

Context-aware technology provides a useful tool to the business world, especially the cellular business. Knowing the location of users enables an effective information push to the users' mobile devices, such as local time and weather, or sales promotion details in a shopping mall, or the direction to the nearest vacant parking spots. In SH environment, context-aware applications initiate a reconfiguration of services according to the context of the mobile Things. For example: a person carrying a Bluetooth enabled cellphone is detected by a sensor node when entering a room, the sensing is followed by an authentication service through the credentials registered in the cellphone to confirm a valid entry, a lighting control service is activated to first consult a home management service on the preferred light intensity for that particular person, it then sets the dimmer to the required level and turns on the lights in that room, a new video content has been bought by another member of the room and is set as shared to everyone, so the media management service initiates a message service to push a message to the cellphone to alert the new addition of video content, the person responses to the message and confirms a play action, the media management service then proceeds to play the movie after configuring the TV, video player and audio amplifier. Context-aware technology is literally the groundwork for building intelligent home.

Activity recognition has long been an active research topic in Computer Science for decades where human activities are recognised and predicted by classifying those feature-extracted data from passive and active sensors. Probabilistic models such as Hidden Markov Model (HMM), fuzzy logics, Bayesian networks and many others are useful mathematical modelling tools acting as classifiers to cope with the complex and noisy sensing environment in ambient intelligence (Choudhury et al., 2008). Choosing the correct sensors and classification algorithms for recognising different activities is important where the accuracy of recognition may depend extensively from the data collection methods through wearable and non-wearable sensors, to the level of usability through user acceptance analysis, to privacy protection through data security measures, to the prediction methodologies through comparison of different classifiers (C. H. Lu and L. C. Fu, 2009; Hong, Suh and S. J. Kim, 2009; Van Kasteren, Englebienne and Kröse, 2010; Fahad, Tahir and Rajarajan, 2014; Debes et al., 2016). Human's context can thus be accurately detected from activity recognition which has become an important component in context-aware systems.

A practical implementation of context-aware home called the Ubiquitous Home was setup as test bed by Yamazaki (2007). Ubiquitous Home differed from other SH experiments by implementing stationary monitoring and sensing devices such as cameras, microphones, floor and infra-red sensors at every corner of the home space together with a movable robot to collect both passive and active data. Middleware communicated between servers and databases so as to configure corresponding services according to the context. This was a large scale deployment of sensors in a real home space to verify context-aware SH technologies, and the setup helped collect data for analysis. For real life applications, the use of cameras to detect context may be argumentative in privacy protection.

Ha and Byun (2012) proposed another setup to showcase context awareness using wearable sensors in a home-care environment. A wearable computer in the form of a wrist-watch contained 3-axis accelerometer to detect user's motion, and a built-in radio connecting to Zigbee network provided localisation data based on radio fingerprinting method. All services (e.g. 3D motion detection service, user localisation management service, interface and activation services, etc.) presented as software bundles on an OSGi framework communicated with each other to provide a fall detection system. Recognising human activity such as drinking and eating can be detected through body sound using wearable sensors (Rahman et al., 2015) instead of biometric sensors being directly contacted with human nervous systems.

Other than physical activity recognition, behavioural activity recognition based on affective computing and psychophysiology is also an interesting field catching a lot of researchers' attention under the concept of emotion context awareness (Y. Oh and Woo, 2004; Zhou et al., 2007; Kuderna-Iulian, Marcel and Valeriu, 2009). Emotional context can be extracted through vision-based recognition that detects facial expression based on normal visual spectrum camera, or human posture based on full spectrum or visual depth camera (C. S. S. Tan et al., 2013). Audio-based emotion recognition can be done where affective features are derived from the pitch, energy, amplitude and formant of recorded segments (Bisio et al., 2013). Physiological emotion recognition is a better alternative for quantifying emotional context using vital signal measurements collected from the human bodies, since it is supposedly less affected by emotional self-regulation (Cacioppo, Tassinary and Berntson, 2007; Jerritta et al., 2011; Levenson, 2014).

There is always a conflict between privacy awareness and context awareness. User intervention to balance the two could be a way out but the result will be a downgrade of autonomy. Further research on balancing these two requirements will be necessary in the coming future.

(5) Usability

Usability encompasses the quality of easy to use and easy to learn for non-technical users in a given SH system. Since all Things in a SH are embedded computing devices, the requirement of usability in SH is closely related with the technologies and theory of HCI.

Technological advancement should aim to improve the quality of human life and the usability of new technology plays a vital role for its success. Usability engineering, User Expereience (UX) and many other topics in HCI are major studies to improve the usability of technologies. A user-friendly interface has always been the design goal. A failure in synchronisation between technological advancement and the UI development can turn user-friendliness into user-unfriendliness. Corn (2011) pointed out that people were tethered to the technology treadmill, interacting with technology became a daily activity. Nowadays

SH and IoT are major technologies that tether heavily with humans more than anything else.

International standards for HCI and usability have been developed for many years and only a few of them are dedicated for homes. Evaluation of the usability for a given SH system according to standards is necessary to keep the SH development to the right direction. Moeller et al. (2014) described how the recent drafted guideline from VDE/ITG[14] applies to the usability evaluation of SH environments. The guideline reviews the differentiation between the "easy of use" for usage without error, and the "joy of use" for positive consciousness on the user experience. The common and critical aspects of SH environments are proposed and the corresponding services for evaluation are also suggested. This guideline, according to the authors can be used as a basis for SH system evaluation, as well as a provision for future research questions since the SH technology is far from mature.

Vazquez and Kastner (2012) evaluated usability of SH from an opposite direction, they revealed a self-checking algorithm to detect how users were dissatisfied and disagreed with a given SH system. A shadow system added a "shadow" process to every "normal" process in a given SH system, and the purpose was to validate the performance of the corresponding normal processes. The shadow processes detected the level of dissatisfaction and proposed warnings or adjustment to the normal processes, the settings would be reconfigured automatically or based on user involvement. This system does not provide a guideline for initial system implementation but provides a close loop feedback for improving usability autonomously.

In-situ operations for SH are usually rely on console type interface encompassing displays (e.g. computer monitor, projector, or TV, etc.) and pointing devices (e.g. keyboard and mouse, touch screen, infrared remote controller, etc.). Web services provide convenient ways to support the communication for all basic user interactions through TV with dedicated remote controllers (Epelde et al., 2011). Some researchers repackage computer consoles into a form of electronic mirrors using flat panel displays embedded with cameras, microphones, touch inputs as well as other sensors to keep the computer less visible at home (Hossain, Atrey and Saddik, 2007). Transforming UI to mobile devices increases the mobility but the consideration to fit in all necessary controls in small screen requires special configuration (Tokuda, Matsumoto and Nakamura, 2012). NUI is adopted by many researchers

[14] http://www.vde.com/en/TechnicalSocieties/Pages/ITG.aspx

as a method for SH interaction to meet the easy to learn criteria. Voice activation becomes a natural way to communicate with the SH systems, but the voice sensing facility must be good enough to capture voice from anywhere or at least most areas in homes. A microphone array as the front-end of a vocal interface at home was proposed by Coelho, Serralheiro and Netti (2008). Augmented Reality (AR) provides a more intuitive way for human interaction by augmenting digital information onto the images of the home environment captured by fixed cameras or cameras on mobile phones (S. Oh and Woo, 2009; Billinghurst, Clark and G. Lee, 2015). A user can make an informed decision according to the augmented information on top of the image (Ullah et al., 2012). Gesture detection enables elderly and disabled people to interact with SH system through some AI algorithms, so users only post some simple gestures in front of cameras in order to perform predefined actions (Bien et al., 2005). Gesture detection is a very broad subject which needs in-depth research when the technology applies to all types of people, more research are found in (Grguric et al., 2013). Brain Computer Interface (BCI) has been getting a lot of attention in HCI research which detects electroencephalographic signals (EEG) to control computing devices (Kosmyna et al., 2016; Alrajhi, Alaloola and Albarqawi, 2017). Applying a BCI in the SH is becoming obvious as an alternative to gesture detection, and a BCI can be used by people with very limited body movements at home (W. T. Lee et al., 2013). Recently, a plethora of online social relationship platforms have introduced social networking as a UI for the SH (Nef et al., 2013; Atzori, Iera and Morabito, 2014). Popular social networks such as Facebook, Twitter, Google+ provide the necessary services to link up Things as separate entities. Since Things in SH are already treated as services which can be registered in the social network as entities utilising all facilities supported by the social network platforms. When there is a change in the Things at home, an alert can be sent to the users if the Things are treated as "friends" of the users' personal groups (Kamilaris and Pitsillides, 2010).

Usability engineering has long been a core topic in HCI criticising the effectiveness, efficiency and satisfaction of any UI design, and recently UX treated by many people as the extension of usability has also been catching a lot of attentions. Since D. Norman (2013) proposed the concept of UX in the early 1990s and suggested the seven stages of action as a guideline for user interface design, a new chapter has begun attracting followers to enhance user interaction experience through the user-centred design principle (Preece et al., 1994; Vredenburg et al., 2002). Ubiquitous computing escalates the level of complexity for user interactions between multiple users and multiple computers at the same time, moreover, non-technical users as well as elderly may dominate the user groups which require an intuitive natural interface for proper home automation controls (Resnick, 2013; M. J. Kim et al., 2013; Brich et al., 2017; Jakobi et al., 2017). ISO9241 proposes the definitions for both "usability" and "UX" but there is no formal definition on the relationship between the two terms (Rusu et al., 2015). Achieving the goals with satisfaction seems to be the major concern for usability, and the measurement of human behaviours contributes to the UX quality (Kurosu and Hashizume, 2013). Enhancing usability can also be done through human behaviour prediction thus an aligned system response or a list of choices will be given to users according to the prediction result (Vavilov, Melezhik and Platonov, 2014). As we have discussed in 3.2.2, activity recognition is a current research topic using mathematical models to predict human behaviours based on input collection from passive data such as RFID (Fortin-Simard et al., 2015) or dynamic audio/video based content (Mitchell, Morrow and Nugent, 2014). Promising results were shown from various prediction methods such as artificial neural network (Zheng, H. Wang and B. Norman, 2008), affective computing (Cu et al., 2010), big data algorithm (Azzi et al., 2014) and deep learning algorithm (Fang and Hu, 2014).

More research is needed to find the right approach to interact humans with the SH system, with the objective for a high degree of usability. Standards for usability are critical for the whole IoT for SH paradigm, and a cross-platform collaboration between engineering science, behavioural science and psychological research is clearly unavoidable.

(6) Security and Privacy Protection

Security and privacy concern the level of protection against malicious attacks and any unauthorised use of private information and they have always been a huge challenge in cyberspace. Stealing confidential materials from business servers, personal photos from private clouds, video content from IP-connected home cameras are typical examples of Internet hackers breaking security. Sharing personal shopping habits, revealing the whereabouts of people and exposing personal details to unauthorised third parties are common behaviours affecting privacy. SH will definitely amplify the impact of the challenge by multiplying the numbers of connected devices and services to the Internet. While link-level security is useful, end to end security is most desirable.

Islam, Shen and X. Wang (2012) claimed that security protection had to be embedded into each node of WSN since every node could be a target for security attack. A list of requirements for a secured systems was revealed: "confidentiality, integrity, freshness, availability and authenticity". Cryptographic techniques were explained as the key technology for security protection along with the descriptions of the different types of security attacks with suggested solutions. The authors also divided privacy into data-oriented and context-oriented which corresponded to the attack of the data content itself by internal or external adversaries, and the attack of the locations or timing of the data collection respectively.

Although most of the existing WSN technologies claim to provide certain security mechanisms, systems integrating contemporary WSN technologies may have vulnerable points not visible or obvious with individual technology for easy security attacks. The leaks from the weakness of each communication technology involved in a complete SH system add up to a new picture of security threats. A real life example showing the vulnerability of a SH network using WiFi protocol for data communication and DECT (Digital Enhanced Cordless Telecommunications) protocol for digital voice communication was demonstrated by Sanchez et al. (2014). The authors revealed the easy detection of B-Field and PP frames from DECT transmission packets when even the latest encryption was implemented. This information supplied context-aware information to attackers, for example, when and where a call was made and for how long. A simple setup using a sniffer near the radio coverage of a WiFi network can capture the MAC addresses and analyse the patterns of the encrypted data packets in order to make a smart guess on web sites visited. New strategies for security and privacy protection are therefore necessary to protect the system as a whole entity by adding all threats from individual technology.

Modern identity technologies (IdM) have been of paramount importance in enabling complex services across a single or multiple domains. Within modern identity approaches, the federated identity and the user-centric models are the most successful ones. Both of them have peculiarities that make their adoption suitable for IoT SH (Fremantle et al., 2014). Federated identity requires human intervention for setting up a circle of trust (CoT) around an identity provider. Services should be registered in that CoT in order to fetch identity information about clients. User-centric identity, where user can be either a real user or a service, is more flexible that federations since the user can combine identity provider credentials (subject to verification) with asserted preferences. In both cases, the identity conveyed to services (or devices providing a service in the context of IoT) is a set of attributes that can be standard or application specific. On top of these identity technologies, other traditional services can be built as authentication, authorization, access control. Due to the heterogeneity present in IoT environments, this kind of security solutions contribute not only providing security services but also serving to other purposes as service discovery and preference assertion.

Nevertheless, state of the art identity systems as Security Assertion Markup Language or SAML (Organization for the Advancement of Structured Information Standards, 2005) or Info Cards, are way too complex for small devices. Further research on adapting these systems to IoT environments should be conducted.

The cornerstone of security systems is trust. IdM systems manage trust in different ways as stated in (Maler and Reed, 2008), but it is always handled in a very static fashion. For instance, SAML and Shibboleth employ pre-existing trust relationship usually based on PKI (Public Key Infrastructure) so a federation implies the aggregation of large lists of providers that agree to use common rules and contracts being hard to deploy and maintain, and high dependence on central authorities (Arias Cabarcos, Almenárez Mendoza, Marín-López et al., 2009). OpenID considered initially a trust-all-comers model but newer versions are dealing with trust establishment. IoT environments need to overcome that trust staticity allowing new things to be added to the ecosystem and allowing new users to interact (securely) with them. To accomplish that trust management and establishment there are two different approaches to be considered trust management and trust negotiation.

IoT SH is and will be a high dynamic ecosystem with a high rate of replacement and new comers, so is worth to handle trust management dynamically by mimicking humans' behaviour so considering the history of interactions, the context, and the scope to derive trust levels for every request (Almenárez Mendoza et al., 2008; Y. Wang and Vassileva, 2003). Moreover, to enable new things and users to be seamlessly incorporated into the system, fair Peer-to-Peer (P2P) trust negotiation schemas are necessary (Bertino et al., 2006; Díaz-Sánchez, Marín López et al., 2008). This kind of trust negotiation systems are able to authenticate and authorize estrangers, relying on the fact that any resource is protected by a policy that expresses which credential(s) should be disclosed to obtain access to it. Other works, as (Arias Cabarcos, Almenárez Mendoza, Gómez Mármol et al., 2014), successfully propose dynamic identity federation systems based on trust management and risk assessment.

Finally, when it comes to the user protection, one of the most worrying problems of IoT is privacy especially when devices are off-loading tasks to the cloud. Letting a device to transfer personal information as habits, media or preferences requires user consent. That user consent is considered granted upon user acceptance of the service level agreement or license bound to the device. The problem is that effectively analysing agreements and contracts could be overwhelming for average users and personal information may have a second life on the internet even after the device is no longer used. Current security framework, even the most sophisticated ones as IdM systems, are not ready to cope with user consent revocation so users may lose control over the use and flow of their personal information (Ryan, 1967). Revoking consent is the ability to grant or withdraw consent of specific actions over data to certain entities and is part of the privacy rules described by the OECD (Organization for Economic Cooperation and Developments) principles and GLBA (Gramm–Leach–Bliley Act), and the COPPA (Childrens Online Privacy Protection Act). IoT solutions for SH should cope with user consent whenever user data is transferred outside the boundaries of the home environment.

(7) Intelligence

Intelligence in SH is the ability to predict human behaviour from the collection of raw data, the management of information, the learning of past experience, the understanding of the surroundings, and the adaptation to dynamic environments. The definition derived from the concepts of knowledge management and the meaning of human intelligence is "*Human Intelligence, mental quality that consists of the abilities to learn from experience, adapt to new situations, understand and handle abstract concepts, and use knowledge to manipulate one's environment*"[15].

Data flood is a big challenge when static web pages migrate to dynamic in the web 2.0 revolution where user-generated content contributes to additional data sources. IBM[16] reviews that 2.5 quintillion bytes of data are created everyday and IDC[17] also shows that the digital universe is growing 40 percent a year. The challenge may rely on good management and intelligent use of huge amounts of data generated from IoT. AI, semantic reasoning and other semantic technologies will help transform data into knowledge and some researchers

[15] http://www.britannica.com/EBchecked/topic/289766/human-intelligence
[16] http://www-01.ibm.com/software/data/bigdata/what-is-big-data.html
[17] http://www.emc.com/leadership/digital-universe/2014iview/executive-summary.htm

in these areas are making significant progress. Although recent research, such as deep-learning, has shown promising results to get machine intelligence closer or even surpasses humans in certain areas, the final intelligent actions based on derived knowledge still relies on humans in a human-centric technology like SH.

Recent research on building intelligent SH systems comes towards SOA where devices become services though abstraction which wraps device functionality into machine understandable format. A typical SOA for intelligent SH system is depicted in Figure 3.4 which shows how middleware technology interoperates with various services from heterogeneous connected devices. Middleware is usually deployed as a Mulit-Agent System (MAS) with each software agent performing unique interoperation between services autonomously inside intelligent system platforms (Liang et al., 2008; Pahl et al., 2009).

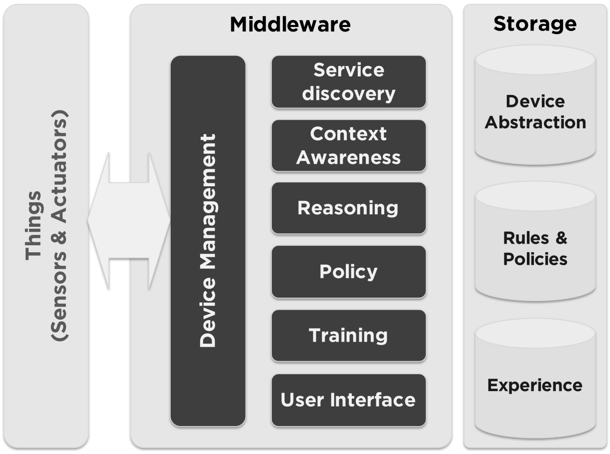

FIGURE 3.4: Typical SOA for intelligent SH system

Connected Things are usually deconstructed into services in terms of individual function or group of functions from a particular Thing or an integration of Things through a device management agent. Chin, Callaghan and Clarke (2009) introduced a concept of decomposing appliances into "atomic" network services using ontology description language, and a new appliance became Meta-Appliance (MAp) which integrated functions from different appliances and other software applications. Context-aware agents kept track of the context for each service and make sure the corresponding service was available when other agents requested. The UI agent used a goal-driven input from users or other services as requirements and activated the service management agent to meet the goal. Each service or device abstraction was registered as a machine readable entity using ontology based description languages so service management agent could initiate semantic reasoning and take actions according to predefined policies. Policies were normally based on AI tools such as artificial neural network, Bayesian network, etc. Decisions were presented as automation or feedback through user interface, at the same time the results were archived as input for machine learning agent to get the system much smarter through training from past experience. Fabbricatore, Boley and Karduck (2012) demonstrated how reasoning, learning and user feedback could work together in a close-loop intelligent resource management framework.

An interesting idea to push all intelligent services to the cloud was found from J. Chen et al. (2014). The authors added one more member to the XaaS with WaaS (Wisdom as a Service) which implemented the DIKW (Data-Information-Knowledge-Wisdom) hierarchy on a cloud computing platform. Local captured data was forwarded to the cloud services which provided all necessary middleware and intelligent services. Results were sent back to users through an Internet connection. Resources in a central shared architecture over the cloud are much larger than an individual SH system, but the response time, connection robustness, and security remain major concerns.

Referring again to section 3.2.2, the prediction of human behaviours using activity recognition becomes a key enabler for ambient intelligence, and user preferences and habit tracking is among the most important tasks in SH. User habits tracking in SH may benefit from TV and media recommendation systems and should explore these solutions to improve user experience. Solutions are typically classified in two categories attending to the recommendation mechanisms (Adomavicius and Tuzhilin, 2005) that are content based filtering and collaborative filtering. The first uses the past experience to propose new actions and the second tries to find similar profiles to determine the most probable desired actions. Many other hybrid approaches allows combining both categories. However, there are other problems to be addressed in SH that are not present in other systems as individual identification, minor detection, group preference modelling, guest detection and presence detection that should be further developed. Moreover, this aligns to security and access control and trust management for addressing guests requests.

Prediction of user behaviour could be the most important criteria for setting the level of SH intelligence (Alam, Reaz and Ali, 2012; Mahmoud, Lotfi and Langensiepen, 2013). AI based mainly on statistical classification methods (e.g. Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbour (KNN) and Meta-multiclass (MMC), etc.) empowers the prediction of human behavioural activities which assists context awareness algorithm (see 3.2.2) in making home automation decision (Verma and Tiwary, 2014; Kragel and LaBar, 2014). User behaviour, especially emotional behaviour hypothesised as the somatic marker by Damasio, Everitt and Bishop (1996), affects individual decision or response to a computer interaction (Debes et al., 2016). Emotion recognition has been extensively researched in multidisciplinary areas of study such as psychology, psychophysiology, neuroscience, biomedical engineering, machine learning, and they focus mainly on data collection methodologies and the classification algorithms with the predicted emotion states as the output of recognition. Theoretical research builds the groundwork for emotion recognition using response patterning with those emotional features such as facial expression (Ekman, 1993), prosodic context (Yadav and Rao, 2015), or ANS specificity (Levenson, 2014). Pattern classification analysis (PCA) based on the hypotheses of ANS specificity (Friedman, 2010) and basic emotions (Ekman, 1992) are the common emotion recognition methodologies using the physiological features mentioned above as ground-truth training datasets to establish the rules for the chosen classifiers (Iliou and Anagnostopoulos, 2009; Stephens, Christie and Friedman, 2010). Due to the noise embedded in the collected physiological response data, complex algorithms based on univariate or multivariate statistics are normally used to increase the prediction accuracy. However, simple pattern comparison using a few physiological signals feeding to a simplified binary classifier or even using truth table minimisation as a decision tree for emotion recognition is possible (C. C. Lee et al., 2011; Raviv, 2013). The criterion for the binary classifier could be extracted from previous empirical studies on psychophysiological research with signal trends of common vital signals such as heart rate, skin conductance, and fingertip temperature act as ANS patterning for emotion recognition (Hönig, Batliner and Nöth, 2007; Kreibig, 2010).

Without a high degree of intelligence, the SH idea may fall back into a home automation concept (Yamazaki, 2006). However, a cross disciplinary research with the help from AI technologies is needed in order to seamlessly and intelligently interact human beings with SHs.

3.3 Summary

This section reviews the collection process of the major contemporary IoT technologies to building SH, and the classification of them according to the proposed requirements. A list of technologies was compiled based on an analysis of the articles retrieved from an online literature search. IEEE Xplore[18] was chosen as the sole source for the literature search on IoT technologies for SH due to two main reasons: (1) IEEE supplies an up-to-date collection of technical papers in a wide range of technology related desciplines, and (2) IEEE Xplore provides an effective search engine allowing the search and download of a database in .cvs format for all articles matching the search criterion. The database contained all metadata of the articles including titles, name of journals, publication years, author keywords, etc. Additional articles were hand picked from other academic journals (e.g. Elsevier, Springer, MDPI, etc.) to fill up the missing references for further explaining the usage of the related technologies. Figure 3.5 depicts the literature search flow and the corresponding statistics of articles in terms of technology categorisation.

SH and IoT are extremely popular research topics and a recent article search from google scholar[19] has produced more than 100,000 articles for *"smart home"* as keyword while *"iot"* returned a result of more than 700,000 articles (this search was done at the end of December 2017, with both *patents* and *citations* options unchecked). Therefore, the current research chose not to do a complete survey on both concepts but only focused on SH and used one major publisher with a wide range of topics specialising in technology research. In order to control the number of articles to be feasible for analysis in a restricted time frame, and allow the latest technologies to be reviewed, the publication year was also limited to the recent ten years from the started date of the current study (i.e. from 2007 to 2017). 2667 articles were retrieved through the IEEE Xplore search engine, and a categorisation was finally done on 1732 articles after removing those without author keywords or the keywords were not technology related. Author keywords are normally used to describe the content of individual article in a very precise form with major concepts represented as common technical terms especially in technical papers. Microsoft Excel was used to analyse the database through (1) extracting only the keywords from the original cvs file, (2) removing blank rows (i.e. articles without author keyword), (3) assigning common technical words to represent related technologies (for examples, using *wireless sensor networks* for "Zigbee" or "Z-Wave" or "BLE", using *artificial intelligence* for keywords such as "pattern recognition" or "SVM" or "prediction", etc.), (4) performing sorting and counting for categorisation of technologies. Major technologies for building the SH have been obtained through the categorisation of the

[18] https://ieeexplore.ieee.org/Xplore/home.jsp
[19] https://scholar.google.co.uk

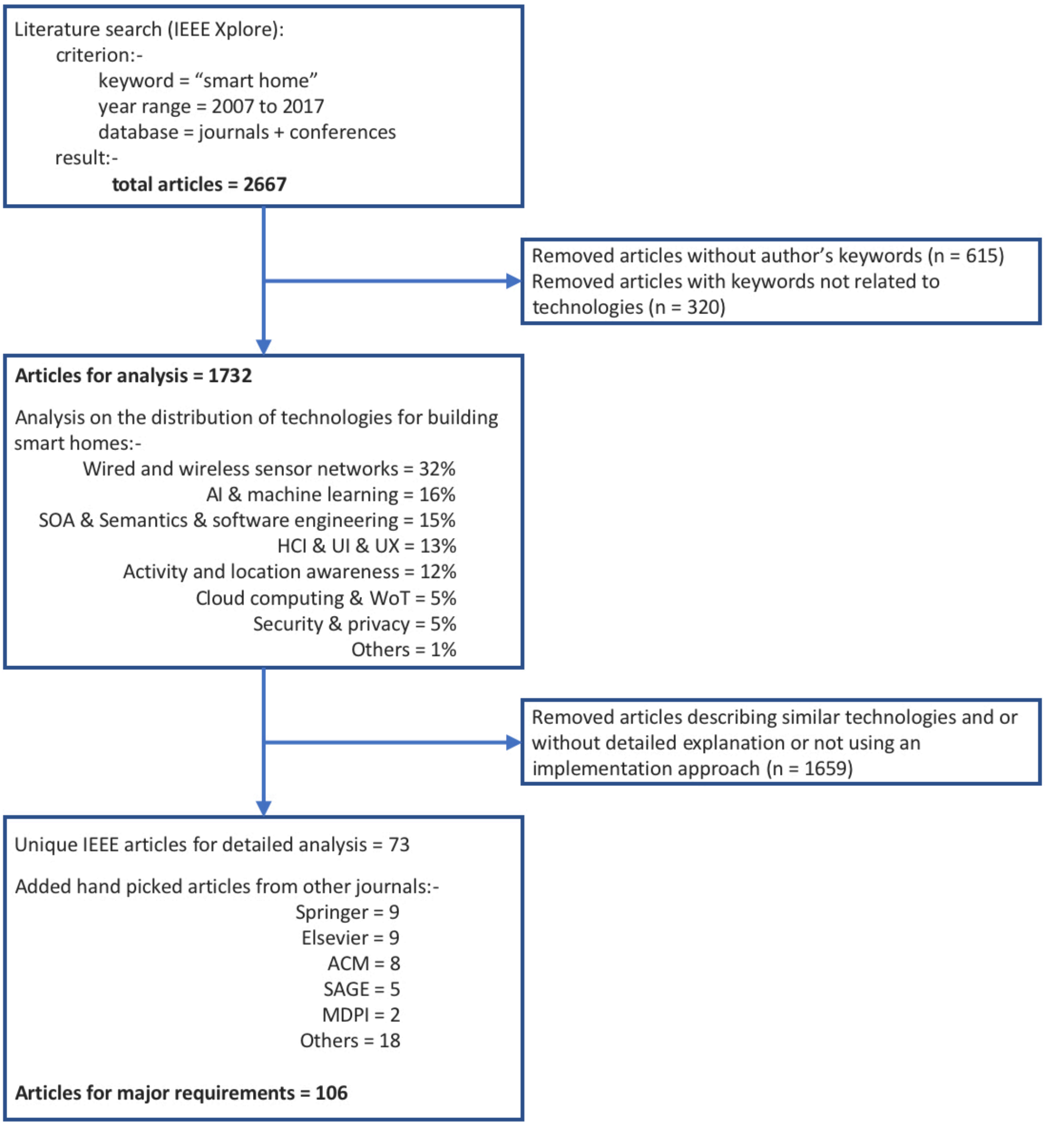

FIGURE 3.5: Literature Search Flow

author keywords of the collected articles and they are listed below:

(a) Wired and wireless sensor network

(b) AI and machine learning

(c) SOA, semantics and software engineering

(d) HCI, UI and UX

(e) Activity, location and behaviour awareness

(f) Cloud computing and Web of Things (WoT)

(g) Security and privacy

(h) Others

Convert the above categories of technologies to a list of requirements for building SH are straight forward for items (b), (d), (e) and (g). Item (b) "AI and machine learning" can be grouped into a requirement of *intelligence* since they enable a prediction of outputs (or responses) through computational statistics from trained classifiers based on machine learning algorithms. Item (d) "HCI, UI and UX" can be grouped into a requirement of *usability* since they provide methodologies for intuitive interaction between humans and computers. Item (e) "Activity, location and behaviour awareness" can be grouped into a requirement of *context awareness* since they concern the detection and recognition of the changes of the contexts which are utilised to trigger actions for home automation. Item (g) "Security and privacy" technologies protect the Things in SH not to be maliciously or accidentally attacked by unauthorised parties since all the Things are normally accessible through any Internet connection, thus, a requirement of *security and privacy protection* is established.

The conversion of items (a), (c) and (f) into separate requirements is a bit tricky since these technologies empower several qualities for building SHs in different scales. There were a few keywords being used repetitively for describing these technologies from the analysis of the author keywords, and they were "adaptive", "scalable", "extensible", "ubiquitous", "pervasive", "heterogeneous", "configurable", 'self adjusting" and other words with similar meaning. However, a deeper investigation on those articles discovered that those words were describing similar classification of technologies but in different scales or different applications. These words were explaining the technologies on hardware levels or networking protocols when they applied to wired or wireless sensor networks. When they applied to software or system configuration such as programming or server task scheduling, they were referring to different scale of applications from managing single home router, to communicating through TCP/IP to a global web service architecture. Three requirements are used to classify these technologies and they are *heterogeneity*, *self configurable*, and *extensibility*. All technologies listed in items (a), (c) and (f) are involved in these three requirements for building SH, and a detailed explanation is found from the previous section.

The last item (h) "Others" was discarded from the current literature review since it referred to technologies not directly related to the building of SH, for examples, traffic management algorithms and technologies related to electric vehicles. Detailed descriptions on how the technologies apply to building SH can be found from section 3.2.2. Overlapping is found where one technology can help build SH and meet multiple requirements, thus a cross reference chart is used here to clarify the relationship. Table 3.1 provides a summary of requirement dependence on different technologies, and the corresponding examples and references for each individual technology category are illustrated in Table 3.2.

TABLE 3.1: Dependency of requirements to technologies

Technology Dependence	Heterogeneity	Self Configurable	Extensibility	Context Awareness	Usability	Security and Privacy	Intelligence
1. Wired sensor networks	✓✓	✓✓	✓	✓	✓	✓	✗
2. Wireless sensor networks (WSNs)	✓✓	✓✓	✓✓	✓	✓	✓	✗
3. Mesh networking	✓	✓✓	✓✓	✓	✓	✓	✗
4. Indoor localisation	✗	✗	✗	✓✓	✓	✓	✓
5. Wed of Things (WoT)	✓✓	✗	✗	✓	✓	✓	✓
6. Service Oriented Architecture (SOA)	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓
7. Cloud computing	✓	✓	✓✓	✓	✓✓	✓✓	✓✓
8. Software engineering	✓✓	✗	✓✓	✓	✓	✓	✗
9. Human Computing Interaction (HCI)	✗	✗	✗	✓	✓✓	✓	✓
10. Activity recognition	✗	✗	✗	✓✓	✓✓	✓	✓✓
11. Identity Management (IdM)	✗	✗	✗	✓	✓	✓✓	✓
12. Artificial intelligence (AI)	✗	✗	✗	✓	✓✓	✓	✓✓
13. Recommendation methods	✗	✗	✗	✓	✓✓	✓	✓✓
14. Semantics	✓	✓	✓	✓✓	✓✓	✓	✓✓
Legend: ✗ = independent; ✓ = least dependent; ✓✓ = most dependent							

3.4 Challenges

Research corporations around the world have been heavily promoting IoT and SH based on an assumption of a huge potential of businesses in almost every market. Governments and institutions are investing immense amounts of resources to put the technologies in place for delivering IoT and SH services to the general public. However, there are still challenges that need to be addressed prior to a full SH and IoT implementation.

3.4.1 Standardisation

Although SH systems are domestic systems with most connected devices, such as appliances or sensors, locally installed. Mobile devices for instance smart phones, tablets and wearables travel from home to home, countries to countries. International standards must be established to govern from hardware interface, to communication protocols, to ontology description language, to semantic rules, to middleware. Standard developing organisations all around the world are proposing international standards for IoT and SH, examples are OneM2M[20] from Europe and Asia, and IEEE P2413[21], etc. The initial release of the OneM2M specifications has just been announced recently and the first draft of P2413 is expected to

[20] http://onem2m.org/

[21] http://standards.ieee.org/develop/project/2413.html

TABLE 3.2: Typical examples and references for each technology listed in Table 3.1

Technologies	Typical examples and Cross references
1	Wired sensor network: bus network (CEBus/KNX/LonWorks), power-line communication (X10/KNX/Insteon/Ethernet, etc.) (Dressler, 2008; Alam, Reaz and Ali, 2012; Withanage et al., 2014)
2	Wireless sensor networks: short range - Zigbee/Z-Wave/BLE, cellular networks-3G/LTE, capillary networks, etc. (Stankovic, 2008; Bein, 2009; Akbal-Delibas, Boonma and Suzuki, 2009; Brown and Sreenan, 2013; K. H. Chang, 2014; Allen, Forshaw and Thomas, 2017)
3	Mesh networking: Zigbee, Z-Wave, BLE, 6LoWPAN, etc. (Cuomo, Melodia and Akyildiz, 2004; Hwang, 2009)
4	Indoor localisation: proximity sensing, radio fingerprinting, space tracking, etc. (Yamazaki, 2007; C. H. Lu and L. C. Fu, 2009; C. Lu, Wu and L. Fu, 2011; Fortin-Simard et al., 2015)
5	Web of Things (WoT): REST, SOAP, WS-*, HTTP, CoAP, etc. (Perumal et al., 2008; Guinard, Trifa and Wilde, 2010; Ye and J. Huang, 2011; Soliman et al., 2013)
6	Service Oriented Architecture (SOA): gateway, OSGi, middlewares, software agents, discovery services, etc. (Li and G. Xu, 2008; Liang et al., 2008; Álamo and Wong, 2008; Pahl et al., 2009; H. Y. Huang, Teng and Chung, 2009; Díaz-Sánchez, Almenárez, Marin et al., 2011; Maternaghan and Turner, 2011; Hachem, Teixeira and Issarny, 2011; Götze, Kattanek and Peukert, 2012; Tokuda, Matsumoto and Nakamura, 2012; Englert et al., 2013)
7	Cloud computing: XaaS, media cloud, Fog computing, etc. (Perumal et al., 2008; Díaz-Sánchez, Almenárez, Marin et al., 2011; M. Tan and Su, 2011; Bonomi et al., 2012; Van-Dang and Y. Kim, 2014; J. Chen et al., 2014; Igarashi et al., 2015)
8	Software engineering: Actor models, Dataflow models, etc. (Cetina et al., 2009; Vavilov, Melezhik and Platonov, 2014; Díaz-Sánchez, Sherratt et al., 2015; Brich et al., 2017)
9	Human Computer Interaction (HCI): UI, BCI, gesture recognition, usability, UX, etc. (Preece et al., 1994; Leeb et al., 1996; Vredenburg et al., 2002; Cacioppo, Tassinary and Berntson, 2007; Hossain, Atrey and Saddik, 2007; Coelho, Serralheiro and Netti, 2008; S. Oh and Woo, 2009; Kamilaris and Pitsillides, 2010; S. Y. Chen and Y. F. Chang, 2010; Maternaghan and Turner, 2011; Corn, 2011; Epelde et al., 2011; Vazquez and Kastner, 2012; Ha and Byun, 2012; Ullah et al., 2012; Grguric et al., 2013; M. J. Kim et al., 2013; Kurosu and Hashizume, 2013; Nef et al., 2013; D. Norman, 2013; Resnick, 2013; W. T. Lee et al., 2013; Moeller et al., 2014; Van-Dang and Y. Kim, 2014; Rahman et al., 2015; Billinghurst, Clark and G. Lee, 2015; Rusu et al., 2015; Kosmyna et al., 2016; Alrajhi, Alaloola and Albarqawi, 2017; Jakobi et al., 2017)
10	Activity recognition: sensor pattern matching, affective computing, behaviour prediction, etc. (Schilit, Adams and Want, 1994; Y. Oh and Woo, 2004; Zhou et al., 2007; Hönig, Batliner and Nöth, 2007; Choudhury et al., 2008; Hong, Suh and S. J. Kim, 2009; Kuderna-Iulian, Marcel and Valeriu, 2009; Friedman, 2010; Kreibig, 2010; Jerritta et al., 2011; Bisio et al., 2013; Valladares et al., 2013; Levenson, 2014; Yadav and Rao, 2015; Debes et al., 2016)
11	Identity management (IdM): federated identity, user-centric models, trust management, etc. (Ryan, 1967; Bertino et al., 2006; Almenárez Mendoza et al., 2008; Díaz-Sánchez, Marín López et al., 2008; Maler and Reed, 2008; Arias Cabarcos, Almenárez Mendoza, Marín-López et al., 2009; Islam, Shen and X. Wang, 2012; Díaz-Sánchez, Almenárez, Marín et al., 2014; Stojmenovic, 2014; Atzori, Iera and Morabito, 2014; Fremantle et al., 2014; Arias Cabarcos, Almenárez Mendoza, Gómez Mármol et al., 2014; Sanchez et al., 2014)
12	Artificial Intelligence (AI): Bayesian network, ANN, deep learning, etc. (Bien et al., 2005; Yamazaki, 2006; Zheng, H. Wang and B. Norman, 2008; Iliou and Anagnostopoulos, 2009; Cu et al., 2010; Van Kasteren, Englebienne and Kröse, 2010; Stephens, Christie and Friedman, 2010; C. C. Lee et al., 2011; Fabbricatore, Boley and Karduck, 2012; Mahmoud, Lotfi and Langensiepen, 2013; Raviv, 2013; C. S. S. Tan et al., 2013; Azzi et al., 2014; Fang and Hu, 2014; Fahad, Tahir and Rajarajan, 2014; Kragel and LaBar, 2014; Verma and Tiwary, 2014; Debes et al., 2016)
13	Recommendation methods: content based and collaborative filtering, etc. (Y. Wang and Vassileva, 2003; Adomavicius and Tuzhilin, 2005)
14	Semantics: Ontologies, SensorML, reasoning algorithm, etc. (Aloisio et al., 2006; J. Xu et al., 2009; Akbal-Delibas, Boonma and Suzuki, 2009; Chin, Callaghan and Clarke, 2009; Hachem, Teixeira and Issarny, 2011; Kao and Yuan, 2012; Mitchell, Morrow and Nugent, 2014; Rubio-Drosdov et al., 2015)

be released in early 2016, so industry will still take some time to adopt the standards and produce consumer products.

3.4.2 Security and Privacy for Smart Homes

Enough examples of security and privacy violation have demonstrated the vulnerability of the existing Internet. IoT actually expands the Internet to a much wider scale which represents an even higher degree of risk. As we have described in the previous sections, new threats will become obvious when heterogeneous technologies are connected together. Research on security and privacy in a new dimension to include end to end system protection as a whole must be considered.

3.4.3 User Interfaces for Pervasive Computing

There is numerous research on the underlying IoT technologies, but the corresponding technological advancement on UI development is catching comparatively less attention. HCI has been providing concepts and theories for computers to interact with humans, and most of them are targeted to single computer interaction. Ubiquitous computing or pervasive computing creates a new working relationship between humans and computers, both the quantity and the quality of computers are much different from the previous generation. Interaction with pervasive computing becomes a new experience thus new research for novel UI design is needed.

3.4.4 Internet of People

With the help of IoT, the Internet is expanding at an unprecedented scale connecting people all over the globe and even outside the globe (e.g. Interplanetary Web (Pendyala, Shim and Bussler, 2015)). Internet connectivity has become an integral part of our daily life, especially the millennial generation. IoT pushes the Internet connectivity to a new level that people are connected no matter they like it or not. The executive chairman of Google, Eric Schmidt, predicted that the Internet would disappear since nobody would notice the existence of the connection in the IoT world. Recent research is focusing on IoP based on IoT technologies since this is a new challenge for humans to interact with so many Things at the same time. Miranda et al. (2015) realised the importance of humans with technologies and proposed a reference architecture for IoT developers and researchers to consider the relationship between humans and IoT systems. The ultimate goal of the IoP may come from a transition of the disappearing of computers (or pervasive computing) to the disappearing of Internet to the disappearing of interface and finally humans and Things are seamlessly connected in a natural way.

3.5 Conclusions and Future Work

This chapter has recommended a list of major requirements for building SH system. The seven major requirements proposed have been based on a taxonomy of architectures and technologies adopted in previous research. Meeting these requirements does not equate to a system that everybody will use, but it provides a common platform for building stronger

SH applications. SH adoption rate is still low because there is no incentive for users to upgrade from ordinary homes to SHs, the remote controlling of heaters from offices is a hype rather than a necessity. However, real benefits are seen from saving energy through smart automation, from remote health monitoring for the elderly through tele-care services, and from controlling appliances for disabled persons through gesture interface or BCI.

UI tailor-made for intelligent homes are critical in a human-centric technology like SH. Although HCI has been researched for decades with promising results to interact humans with single computers, a new paradigm for humans interacting with large number of invisible computers at home is a new and evolving topic. Intelligence seems to be the most critical requirement to turn the traditional home automation concept into SH, and the advance in contemporary IoT technologies together with the escalation of processing power of embedded microprocessors may enhance the IoT into IoP where human interaction with Internet connected devices can be intuitive and the corresponding human responses can be predicted.

This chapter lays the groundwork for building intelligent cyber physical space based on IoT technologies. The requirements on heterogeneity, self-configurable and extensibility empower smart sensors to work seamlessly with any computers/servers autonomously where a global sensory system is established. Context awareness, usability and intelligence are three additional requirements escalate this global sensory system to intuitively interact with humans and predict their behaviours. Finally, the requirement of security and privacy protection helps users build trust and confidence in using the system. If sixth sense is the prediction of human emotional behaviour, a global sensory system can sense the context which will affect human emotion from anywhere on earth with Internet connection. Emotional context awareness may be the core ingredient in building an artificial sixth sense system and a detailed analysis on human interaction is needed. Chapter 4 will continue the discussion on how an artificial sixth sense system can be built base on the technologies illustrated in this chapter.

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Chapter 4

Towards Disappearing User Interfaces in Ubiquitous Computing: Human Enhancement from Sixth Sense to Super Senses

This chapter is an enhanced and expanded version of a published position paper illustrating that human sixth sense can be simulated and forecasted using DUI for interacting humans with ubiquitous computers naturally. IoT has become a platform facilitating contemporary technologies to be effectively implemented on the Internet and form a true ubiquitous and pervasive computing platform. This new interaction experience through the IoS concept can turn any connected human to enhance individual sensing capability allowing emotion prediction based on a concept of emotional context awareness. The required technologies to build a smart IoT platform connecting people together is presented in Chapter 3 which is an expanded version of another published paper acting as the technical support for the position paper.

The current chapter also answers the research question of this thesis by showing that DUI integrating with IoT technologies can intuitively interacting with connected humans where human senses may be able to be extended. A hypothesis of predicting human sixth sense is proposed in the conclusion section based on the idea of emotional context awareness.

A version of this chapter has been published in the Springer Journal of Ambient Intelligence and Humanized Computing.

Hui, T.K.L. and Sherratt, R.S. 'Towards disappearing user interfaces for ubiquitous computing: human enhancement from sixth sense to super senses'. Journal of Ambient Intelligence and Humanized Computing 8.3 (2017), pp 449-465, DOI:10.1007/s12652-016-0409-9.

The discovery of human sixth sense electronically is possible when pervasive computers interact unnoticeably with humans in ubiquitous computing. The design of computer user interfaces towards "disappearing" forces the interaction with humans using a content rather than a menu driven approach, thus the emerging requirement for huge number of non-technical users interfacing intuitively with billions of computers in the Internet of Things is met. Learning to use particular applications in ubiquitous computing is either too slow or sometimes impossible so the design of user interfaces must be naturally enough to facilitate intuitive human behaviours. Although humans from different racial, cultural and ethnic backgrounds own the same physiological sensory system, the perception to the same stimuli outside the human bodies can be different. A novel taxonomy for DUIs to stimulate human senses and to capture human responses is proposed, where the application of DUIs is expected to become the tools to discover the human sixth sense.

4.1 Introduction

The growing importance of HCI is a result of the widespread deployment of computers connecting with humans. Early computer users were computer specialists and programmers when the major design goals for computers were processing-power and processing-speed during the time a single mainframe computer occupied a whole room. Usability became a profound issue when personal computers prevailed in the late 70s since personnel and non-professionals had joined the user group with no prior computer science knowledge (Shackel, 1997). Ubiquitous computing proposed by Weiser (1991) as "*The Computer for The 21st Century*," has envisioned future computers to be invisibly living with humans, hence the range of user types has again widened. With the popularity of the Internet in recent decades, the concept of IoT further boosts the applications of ubiquitous computing to connect almost everything electronic to the Internet. The ultimate result is an unprecedented demand for better HCI technology to cope with the needs for the huge number of non-technical users interacting with billions of network-connected computers.

HCI is a multidisciplinary technology that heavily focuses on human-centric UI design (D. Norman, 2013). Extensive research on natural science not only provides extremely functional UIs through tangible and intangible media, but smart algorithms based on computational intelligence also help predict human behaviours through activity recognition; thus tailor-made responses are astutely delivered to individuals. Further enhancement of the HCI's humanisation quality is found from affective computing that enables computers to understand human emotions (Sunghyun et al., 2015; Weerasinghe et al., 2014), and computational humour studies that provides a more relaxing interaction environment (Nijholt, 2014; Nijholt et al., 2006). Collaboration between researchers from applied and social science is the core enabler for a successful multicultural and multi-ethnic HCI design; however, a seamless integration does not always occur. Dourish and Bell (2011) reviewed the current gaps in HCI research for ubiquitous computing from an ethnographic perspective with the conclusion that social and cultural consideration will enhance future HCI design through a socio-technical practice. A novel way to connecting multidisciplinary researchers is equally important as the basic research but is not obvious in the current HCI field.

NUI is an emerging trend in HCI where humans can interact naturally with computers instead of using conventional methods such as CLI or GUI. Despite its high prevalence in both academic research and commercial applications (Bhowmik, 2013), NUIs are criticised as being "*artificial naturality*" and many types of NUIs are not representing natural human behaviours especially gesture based interactions (Malizia and Bellucci, 2012; D. A. Norman, 2010; D. A. Norman and Nielsen, 2010). This chapter reviews the usefulness of NUIs from a different direction by considering only unnoticeable or "disappearing" natural interfaces in ubiquitous computing environments.

DUI is a logical provision of natural HCI and the term "disappearing" in this chapter refers to tangible and intangible UIs that exist and function well but are not noticeable by humans. They are classified into three main categories: (i) human body as DUIs, (ii) edible and implantable DUIs, and (iii) wearable DUIs. Individual HCI technologies and algorithms have been researched with favourable results and they normally target certain functional areas and particular user groups. A novel taxonomy is proposed in this chapter to classify and compare the different types of state-of-the-art DUIs, together with their advantages and disadvantages according to their intended areas of application. Researchers and industry personnel can use this classification as a guideline to select and combine different DUIs to form a holistic natural UI for certain group of users in ubiquitous computing. For example, drivers will be alerted when they are not paying attention to the roads using a speech interface based on abnormal behaviour discovery from visual posture detection, and elderly people with Alzheimer's disease may require constant monitoring of their activities to detect their whereabouts and predict their behaviours with non-invasive and non-intrusive sensors.

An interesting DUI application is to enhance human senses. Researchers relentlessly proposed and proved the existence of extra human sense organs since Aristotle first classified the five basic senses. Physiological comparison of the same sensory type between humans and animals reveals that some animal sensory systems are more sensitive, some of them can even sense the seismic waves before the earthquakes happen. Spiritual sixth sense is a controversial subject that many attempts have been tried to prove without success, but abnormal behaviours such as clairvoyance, clairaudience, remote viewing, etc., keep on happening without logical explanation. Adding new senses and enhancing existing senses by a combination of various DUIs may be a way to turn on human sixth sense or even supersenses.

This chapter proposes a novel taxonomy of DUI technologies from the result of a literature survey on related HCI topics and research. Section 4.2 explains the classification criteria for the DUI technologies with reference to the human inputs and outputs system. Enhancing human basic senses and enabling the sixth sense as an application of DUIs are discussed in section 4.3. Finally we conclude the chapter in section 4.4 with indicators for further research.

4.2 Disappearing User Interfaces

NUI provides an opportunity to enhance user experience by interacting naturally with computers. Technologies such as gesture based detection, voice and facial expression recognition are typical NUI technologies that are promoted as better than traditional HCIs like

CLI and GUI methods which have been claimed as hard-to-learn and hard-to-use for computer illiterate people. Presumably natural human behaviours are the only requirement to effectively use NUI, and no training is required since natural way of interaction should be intuitive. Macaranas, Antle and Riecke (2015) reviewed the 3 major issues undermining the intuition of NUI as (i) no common standard; (ii) unexpected users' experiences; and (iii) lack of affordance. However, intuition is subjective and varies according to cultures and users' past experiences, thus global standard may be indefinable (Malizia and Bellucci, 2012; Lim, 2012).

DUI is a natural HCI focusing on interaction with the contents instead of the interfaces (Lim, 2012). Ubiquitous computing together with the concept of IoT drive the merging of the digital and physical worlds, where information and digital contents are the products communicating in ubiquitous computing networks based on M2M and H2M interactions (Holler et al., 2014). Humans are content receivers through the sensory systems, and at the same time humans are content providers mainly through muscular movements and nervous systems. DUIs enable the conveyance of contents between humans and machines in a natural way through tangible or intangible artefacts; touch or touchless interface; outside or inside human bodies; and most importantly not noticeable by the target persons so the interaction is done based on intuition. DUI is multi-modal in nature by sensing human behaviours through different disappeared UIs in a natural way and creating the contents for exchange. For example: a "content" representing "Peter is going home from his office" is created and delivered to Peter's home server once the combination of spatial and temporal information from the DUIs around Peter agree to pre-set rules and past experience. Peter's home server decodes the content and prepares the services to welcoming Peter; such as warming the house, heating-up the water, preparing dinner, etc.

DUI may become the de facto standard for future miniaturised digital artefacts by removing the requirement of built-in tangible interface. Moore's law has been the driving force in the silicon world for five decades shrinking the size of silicon-based electronics until recently that the benefit of miniaturisation starts to diminish with the uneconomically high cost of lithography at nanoscale (Mack, 2015; A. Huang, 2015). New packaging methods such as 3D-stacking will continue the miniaturisation process after solving the associated problems such as high heat density and low manufacturing yield (Das and Markovich, 2010; Kyungsu, Benini and De Micheli, 2015; Xu et al., 2012). Nanotechnology especially molecular electronics has a high chance to take over the driver seat for the miniaturisation journey despite its controversial and unfulfilled promises during its up and down in the last 40 years (Choi and Mody, 2009; Kelly and Mody, 2015). Recent research shows promising results in single-molecular transistor, DNA computing, and nanotube devices that enables followers of molecular electronics to see the light at the end of the long dark tunnel (Boruah and Dutta, 2015; Strickland, 2016). Micro Electromechanical System (MEMS) technology complements the miniaturisation paradigm by shrinking electronic control and mechanical structure together which fit nicely for DUIs with mechanical sensors or actuators. Miniaturised electronics and MEMS help hide electronic devices on or inside human bodies where wearable, implantable and edible electronic artefacts can interact invisibly with humans and communicate with one another based on Body Area Network (BAN) topology or Internet connectivity with built-in network-enabled facility.

4.2.1 DUI for Human Inputs

DUIs may interact with human inputs mainly through the five basic senses: vision, hearing, touch, smell and taste. Dedicated organs sense the world outside human bodies where sensory transduction produces the corresponding electrical signals and activates the human brain for perception (Henshaw, 2012). The whole "stimulus-sensation-perception" process is dynamic and will be affected by various factors such as the properties of stimulus, the physical environment, the condition of human body and also the human age. Sensory adaptation causes sensitivity adjustment which adapts to the recent perception experience (Webster, 2012; Roseboom, Linares and Nishida, 2015). Sensory changes occur if there is undue impairment on the sensory system, or a change in human weight (Skrandies and Zschieschang, 2015), or most commonly when the sensitivity declines due to ageing (Wiesmeier, Dalin and Maurer, 2015; Humes, 2015). Multisensory integration, acts as a fusion of sensory data, helps increase the accuracy of perception but the application is normally restricted to adults since the development of sensor fusion for humans only starts in pre-teen years (Nardini, Bedford and Mareschal, 2010).

Figure 4.1 shows a typical illustration of a human sensory system and it can be seen that human perception based on the human brain is the result of decoding the sensation signals which are activated by the stimuli coming from the outside world through the basic sensory organs, while human outputs, which will be discussed in section 4.2.2, are the responses to this perception.

(1) Vision

Vision has been the dominant interface between humans and computers since the prevalence of the GUI paradigm where computer generated graphics are displayed on desktop computer monitors using CRTs (Cathode Ray Tubes) or flat panel displays (e.g. LCD, Plasma, OLED, Quantum Dot, etc.). Although desktop computer monitors are still one of the most useful interfacing devices for formal computing, they don't normally fall into the DUI category since they are far from disappearing for normal users in the ubiquitous computing world. Exceptions are found when computer monitors, especially flat panel displays, are embedded into everyday objects or furnitures such as mirrors or window glasses (Jang et al., 2014; Zhen and Blackwell, 2013).

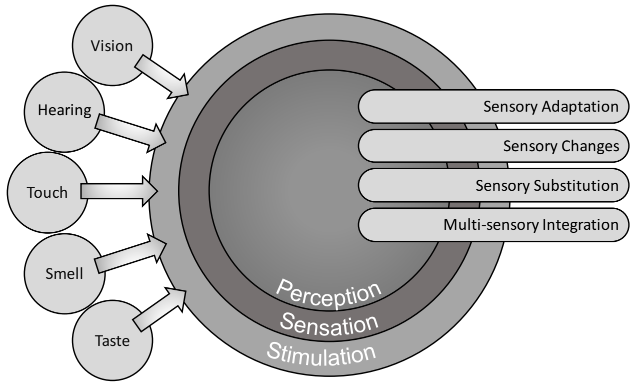

FIGURE 4.1: Human Sensory System

Projection display can be a good candidate as DUI for human vision where computer generated images can be projected onto flat surfaces such as tabletops or concrete walls in indoor or outdoor environments. Together with the sensing of human body part movements, an interactive projection interface is provided on fixed surfaces whenever necessary with single or multiple projectors (Yamamoto et al., 2015; Fleury et al., 2015; Lai and Majumder, 2015). A wearable projector enables image projection onto any surfaces wherever the wearer goes, it can project onto any object in-front of the viewer, or even the wearer's own body (Harrison and Faste, 2014). Mid-air or free-space display technology allows the projection of images without a physical "surface" and various media are proposed to establish non-turbulent air flow of particle clouds in free space as projection screens that viewers can walk-through (Rakkolainen, Sand and Palovuori, 2015).

Considering 3D image projection, viewers wearing passive or active shutter eye-glasses can perceive image depth when stereoscopic technology is implemented in the projection systems. However, research has shown that viewers exposed to image-switching for a certain period will suffer from visual discomfort or even visual and mental fatigue (Amin et al., 2015), thus the wearing of special eye-glasses is not considered as DUI. Autostereoscopy provides glasses-free 3D image viewing using multiple projectors but the complicated alignment of parallax-barrier, lenticular lens or diffuser mechanism on the projection screen is still a big challenge for commercial applications (Lee, Shon et al., 2013; Hong et al., 2011). A true 3D image can be shown in free space using volumetric display technologies. Mid-air laser 3D holograms, composed of visible ionised air molecules as image pixels, are produced by laser-induced plasma scanning display (Ishikawa and Saito, 2008). Recent research on laser hologram using femtosecond laser pulses enables a safer composition so users can touch the image with bare hands for real time interaction but the required instrumentation and setup still belong to laboratories. An interesting volumetric 3D projection display can be found from an assembly of fog-producing matrix and 3D images are projected to selected particle cloud above the dedicated fog-producing element (Lam, Chen and Y. Huang, 2015). Wearable eye-glasses are good alternative DUI for human visual input, and the see through nature of the glasses allows augmented data to be imposed on top of the physical environment in real time (Brusie et al., 2015).

Electronic cotton paves a new path for embedding electronic circuits in textile (Savage, 2012), a fabric display can be made to show simple images on clothing (Zysset et al., 2012).

(2) Hearing

Hearing is another popular human input interface, while computer generated sound in the audio frequency range is delivered through a medium to the human auditory system. Sonic interface is a good DUI for naturally interfacing with humans in open space, and the critical requirement is the delivering of high quality sound signals which can normally be achieved through frequency response equalisation of loudspeakers and/or room acoustics (Cecchi et al., 2015).

Privacy is one of the major concerns in sonic UI, and technologies for directional sound can change the omnipresent nature of normal sound broadcast in open space. Parametric speaker consists of an array of ultrasonic transducers can transmit a narrow sound beam to the location of receivers through modulation of a large amplitude ultrasonic frequency carrier with an audio signal and use phase delaying method to align the beaming direction. The non-linear air medium then self-demodulates and recovers the audio to receiver(s) along the direction of the broadcasting path. Distortion of the recovered audio signals and the directivity are big challenges in this method, while recent research has improved the frequency response through enhancing the transducers as well as pre-processing the audio signal before modulation (Akahori, Furuhashi and Shimizu, 2014; Gan, Tan and Kuo, 2011). Modulated ultrasonic carriers can also be self-demodulated through the human body, thus the privacy is further enhanced since only the person(s) touching with the ultrasonic vibration can hear the original audio signals (S. E. Kim, T. Kang et al., 2014; S. E. Kim, T. W. Kang et al., 2013). Personal sound zone is an active research topic trying to control ambient sound pressure and establish multi-zones in a room where intended sound source dominates the sound field inside a particular sound zone, thus humans staying in that zone will not be interfered by sound sources outside this virtual zone. The requirements of speaker array with large number of directional speakers, and the problem of dynamic acoustic reverberation will be obstacles for turning the idea into general public usage (Betlehem et al., 2015).

Computer generated sound for interfacing with humans can be classified into speech and non-speech audio signals. Natural language processing allows humans to communicate with computers through speech using their own language and recent research in computational linguistics with the support from big data and cloud computing enables a more human-like computer generated speech through machine learning and text-to-speech (TTS) technologies (Hirschberg and Manning, 2015). TTS algorithm with modification on prosodic feature can even provide computer generated speech with emotions according to the context (Yadav and Rao, 2015). Auditory display based on sonification converts data into non-speech sound, such as alert and warning signals; status and progress indications; or data exploration; etc., thus the content of the data initiates human perception through hearing (Thomas, Hunt and Neuhoff, 2011). There is proof that auditory feedback helps synchronise human output based on interactive sonification (Degara, Hunt and Hermann, 2015).

(3) Touch

The sense of touch enables a private communication with computers through the human skin. Three types of receptors: pressure and touch (mechanoreception), heat and cold (thermoreception), and pain (nociception) in the human skin sense the outside world based on mechanical, thermal, chemical, or electrical stimuli (Kortum, 2008). Haptic technology is becoming popular when mobile computing devices such as cell-phones and tablet-computers utilise touch sensitive screens as major input, while Internet connectivity further enables remote touch sensing for tele-operation in the medical field thus operators can remotely feel the patience and the equipments in real time (Gallo et al., 2015).

Contactless touch interface, a good DUI candidate, makes tactile sensation in free space possible through compressed-air, ultrasound, or laser technology. Air-jet tactile stimulation is based on controlling compressed air blowing through focused nozzles but the common problems are limited travelling distance and low spatial resolution. An improvement can be found by replacing direct air flow with air vortex although the generation mechanism of air vortex may be more complex (Arafsha et al., 2015; Sodhi et al., 2013). Airborne ultrasonic tactile display is an alternative for free air tactile stimulation where human skin can feel the pressure from the radiated ultrasound waves in a 3D space using an array of ultrasonic transducers and haptic feedback is possible through a calculation of the phase delay and amplitude for each individual transducer (Iwamoto, Tatezono and Shinoda, 2008; Long et al., 2014; Inoue, Makino and Shinoda, 2015). Carter et al. (2013) has also shown that a special layer of acoustically transparent reflection surface allows an interactive volumetric mid-air touch display. Spatial accuracy is enhanced but the power consumption is relatively higher (Iwamoto, Tatezono and Shinoda, 2008). Laser-induced thermoelastic effect also produces free air haptics but the precise control of laser pulse timing and energy is the most critical factor in safely utilising the technology (Jun et al., 2015; Lee, J. S. Kim et al., 2015).

Wearable touch interfaces can also be considered as DUIs if they are not noticeable after attaching to the human bodies, especially when miniaturisation based on MEMS and new materials enables the complete interface modules be hidden in everyday things humans will carry around (Ishizuka and Miki, 2015; Koo et al., 2008). Jackets or vests with embedded sensors and actuators for vibrotactile, pressure and thermal stimulation are DUIs providing sense of touch to the human bodies. Affective tactile perception can also be accomplished through different combinations of embedded stimuli inside the electro-mechanical clothing, typical examples are hugging (Teh et al., 2008; Samani et al., 2013), bristling (Furukawa et al., 2010), and warm social touch (Pfab and Willemse, 2015), etc. Koh et al. (2011) have proposed a novel idea for a wearable 3D touch interface which uses a dynamic magnetic field produced by electromagnets to control the movements of ferromagnetic fluids.

Electrostatic discharge through the human body can also generate haptic feedback with proper control of the discharge power within safety limits. Mujibiya (2015) proposed a boost up electrostatic charger installed in a grounded shoe to stimulate a tactile feeling when the wearer touches anything grounded to form a closed circuit.

Data Physicalisation, based on an ancient concept of representing data using physical objects, has recently been proposed as a new haptic HCI (Jansen et al., 2015). An idea of physical computing provides flexible and shape changing interfaces which enable a haptic stimulation to the users through a continuous form changing of a physical object or its surfaces according to the data output (Kawahara et al., 2017). This concept is still in an early stage with the standards for input and output to be defined before a practical application can be found.

(4) Smell

Human smell, or olfactory, is a chemical sense and is not as popular as the three basic senses mentioned above for the purpose of HCI. Molecules with molecular weight from approximately 30 to 300 vaporised in free air enter the human nose through the left and right nostrils during breathing, bind to the olfactory receptors and activates the perception of smell in the human brain. The small spatial difference between the two nostrils allows localising the odour similar to the spatial differences in human ears and eyes to detect the direction of the sound source and perceive the image depth respectively. Although decades of research has proposed different versions of odour classification, and also estimated 350 receptor proteins in the human olfactory epithelium, the primary odours are still unknown so digital reproduction of odour is a biggest challenge in computer olfactory interface (Kortum, 2008; Kaeppler and Mueller, 2013). A systematic approach to select and combine different chemical substances for odour reproduction was reviewed by Nakamoto and Murakami (2009) and Nakamoto and Nihei (2013). They made use of "*odour approximation*" technique to choose and blend a limited number of odour components based on their mass spectrum to record and reproduce some target odours. This is not a generic approach but it may fit for specific application areas. Despite the lacking of primary odour, researchers keep spending their efforts proposing architectures and methodologies for local or remote olfactory interfaces, design focuses are laid on tagging different odours to unique objects or photos, combing pre-defined odours to form new scent, and delivering odour messages to remote locations, etc. (Brewster, McGookin and Miller, 2006; McGookin and Escobar, 2016).

Presentation of smell stimuli can be achieved through diffusion to open air but the vaporisation of odour molecules is relatively slow compared to the propagation of mechanical waves in sound and electromagnetic waves in vision, thus a continuous emission of odour vapour is normally applied. However, a long exposure to same stimulus causes olfactory adaptation which declines the sensitivity. Controlling of emission timing and synchronisation with human breathing patterns may help eliminate the adaptation problem but the sensing area will become personal and the corresponding detection of human breath will increase the complexity of the system (Kadowaki et al., 2007; Sato et al., 2009). Installing scent emission facility on existing display systems enables multisensory integration of vision and smell, pores on the projection screen can emit vaporised smell stimuli which synchronise with the dynamic video content although the sensing distance is short.

Scent projector using air vortex can deliver scented air to a longer distance at controlled directions. Double vortex rings from two scent projectors can even stimulate the direction of movement of the scented air (Matsukura, Yoneda and Ishida, 2013; Yanagida et al., 2013). Wearable scent diffuser can also personalise smell stimulation by assembling micro-pumps to deliver liquid odourants for atomisation by SAW (surface acoustic wave) device and vaporise to air surrounding the wearer (Ariyakul and Nakamoto, 2014; Hashimoto and Nakamoto, 2015).

The human sense of smell may also act as an interface for dreaming or emotional priming. Active research has found that using olfactory stimulus can enhance fear extinction during slow-wave sleep condition when same olfactory context re-exposes to humans who have faced contextual fear condition during awake periods (Hauner et al., 2013; Braun and Cheok, 2014). Braun, Pradana et al. (2016) have shown that the addition of olfactory stimulus can significantly modulate emotional perception from past experiences.

Basic research is important to understand how human beings perceive the olfactory sense before primary odour can be agreed by both the researchers studying oflaction, as well as the general public. Classification of odour may involve both physiological and psychological perception through the human chemoreceptors and the human brains (Kaeppler and Mueller, 2013; Joseph and Carlson, 2015).

(5) Taste

Humans sense five different tastes using the taste receptors distributed on the dorsal surface of the tongue: sweet, bitter, sour, salty and umami. The perception of smell (or gustatory), however, relies not only on the chemical sense on the tongue but also the senses of sound, smell and touch (Kortum, 2008; Ranasinghe, Karunanayaka et al., 2011; Obrist et al., 2016; Velasco et al., 2016). Narumi et al. (2011) demonstrated a pseudo-gustatory system influencing the perception of taste using multisensory integration with sensory cues from vision and olfactory, where plain cookies could taste like chocolate with the associated chocolate image and smell exposed to the human subjects under test.

The tongue, sense organ for taste, is heavily used as computer interface based on its haptic nature such as controlling the mouse movements, operating smartphones or wheelchairs, or even convert tactile sensing on the tongue to human vision[1]. However, there are very few computer-taste interfaces, and one of them comes from Ranasinghe, Nakatsu et al. (2012) who proposed a tongue-mounted interface utilising a combination of electrical and thermal signals to stimulate the different taste. An improvement was further reviewed by the same authors to combine smell stimuli for a better perception of flavour (Ranasinghe, Suthokumar et al., 2015).

(6) Extra Human Senses

Since Aristotle first proposed the classification of the five basic human senses more than two thousand years ago, research from anatomy, physiology and psychophysics have relentlessly discovered additional human sense organs such as vestibular, muscle, and temperature senses (Wade, 2003). Humans do have more than five senses and they all fall into the same "stimulus-sensation-perception" process with the human brain as the final decision maker after interpreting the outside world from the stimuli. Despite the nature of stimulus to each type of sense organ is different, the perception can be the same. Sensory substitution is an emerging research demonstrating that brain plasticity enables human brain to choose a particular type of sensor or combination of sensors to arrive the same perception after a training period (Bermejo and Arias, 2015). Examples can be found from previous sections that haptic sensors can replace vision sensors allowing blind people to see the world, or

[1] http://www.wicab.com

sonification enables humans to perceive the content of an analysis without looking into the raw data. DUI should therefore be more effective to interface with human inputs through delivering content instead of raw data, and the more we know the human brain the more we will realise how to interface with humans. Numerous research institutions all over the world are already investing considerable efforts into exploring the human brain[2] [3] [4], thus computer generated stimuli for human inputs will become more effective and precise in the future.

4.2.2 DUI for Human Outputs

DUIs capture human outputs based on monitoring human body activities: body parts movements, body sound generation, body temperature variations, body odour emissions, and the dynamic physiological parameters. The disappearing nature of DUI avoids step-by-step manual driven human interaction, and its focus is set on interfacing with the contents which are the actions generally derived from human perceptions (Lim, 2012). DUI for human outputs is normally based on a "data capture, feature extraction, classification and prediction" process which is the algorithm generally adopted in computational intelligence, and a typical block diagram is depicted in Figure 4.2.

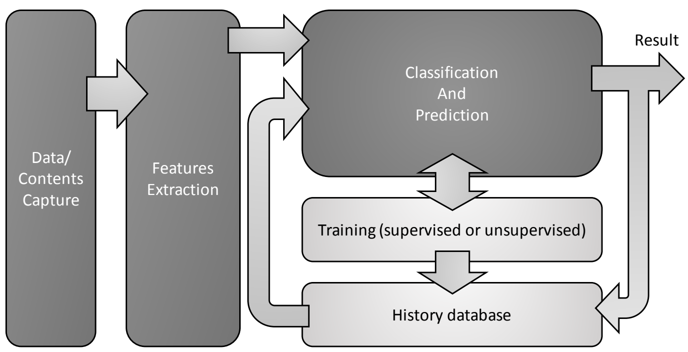

FIGURE 4.2: Typical DUI for Human Output Framework

Discussion in the following subsections concentrates mostly on the DUI front end which is the capturing of human activities, and various data or contents capturing technologies are reviewed according to the nature of the activities. The corresponding feature extraction is application specific which depends on the methodology for activity detection (e.g. same sound clips captured from a human body can be used for voice command using speech recognition algorithm, or medical diagnosis using sound sensing techniques, etc.) and will be mostly skipped in this chapter.

[2]https://www.whitehouse.gov/BRAIN
[3]https://www.humanbrainproject.eu
[4]http://brainminds.jp/en/

Classification and prediction normally adopt probabilistic methods, such as HMM (Hidden Markov Models) or Bayesian network or ANN (Artificial Neural Network), to choose the most possible result according to the extracted features and the past history, and generally supervised or unsupervised training will be followed to increase the prediction accuracy. Four basic types of human outputs are discussed in the following sub-sections together with the explanation of the different capturing methods and technologies. A summary of human outputs and the corresponding capturing techniques is depicted in fig. 4.3 and the cross references for each technique are listed in table 4.1.

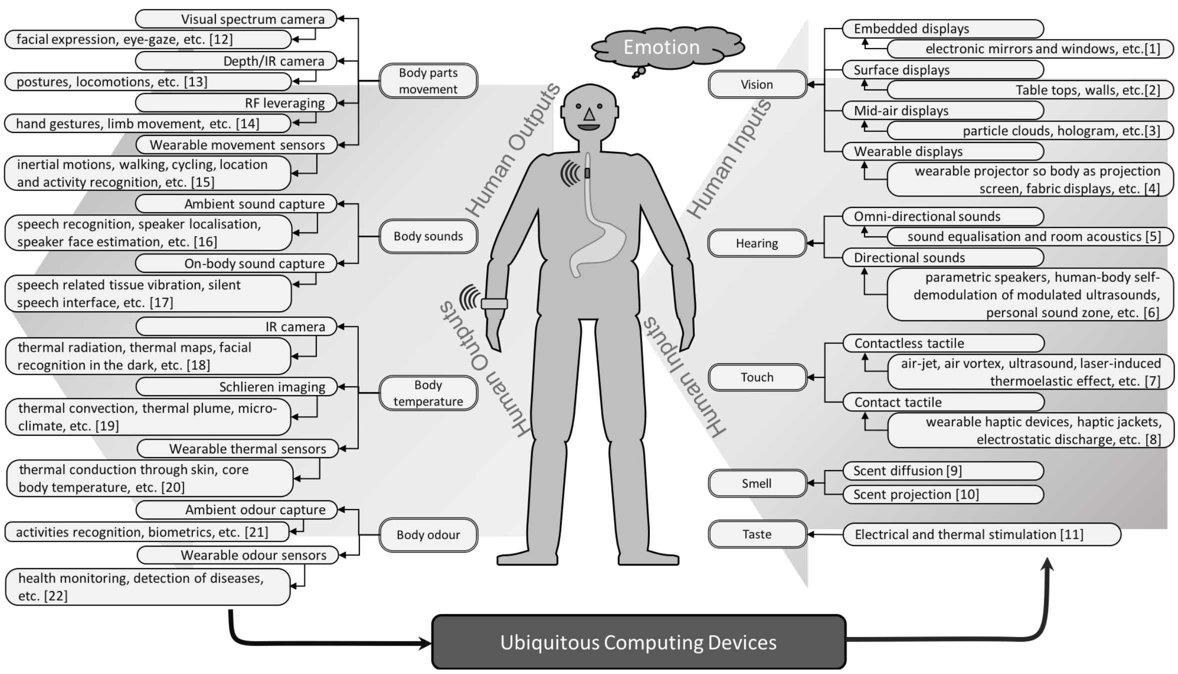

FIGURE 4.3: Human Computer Interaction Map with state-of-the-art DUIs (all numbers listed in the figure refer to table 4.1 for cross references)

(1) Body Parts Movement

Body parts movements are the major human outputs which normally include (i) body postures, (ii) limb movements, (iii) locomotion, (iv) hand and finger gestures, (v) facial expression, (vi) eye gaze, and (vii) body micro-motions. All of these actions are achieved by muscle movements activated by the human brain, and the capturing of these movements normally involves spatial and temporal tracking of the target body parts.

Image capturing through regular visual-spectrum cameras detects the target body parts in fine details which is useful in getting facial expression or tracking eye-gaze. Facial expression is thought to be linked with human emotion and is usually composed by the subtle

TABLE 4.1: Cross references for Human Computer Interaction Map

Number	Cross references
1	Jae Seok et al. (2014); Zhen and Blackwell (2013)
2	Yamamoto et al. (2015); Fleury et al. (2015); Duy-Quoc and Majumder (2015)
3	Rakkolainen et al. (2015); Amin et al. (2015); Hyoung et al. (2013); Hong et al. (2011); Ishikawa and Saito (2008); Miu-Ling et al. (2015)
4	Harrison and Faste (2014); Brusie et al. (2015); Savage (2012); (Zysset et al. (2012)
5	Cecchi et al. (2015)
6	Akahori et al. (2014); Woon-Seng et al. (2011); Sung-Eun et al. (2014); Kim et al. (2013); Betlehem et al. (2015)
7	Arafsha et al. (2015); Sodhi et al. (2013); Iwamoto et al. (2008; Inoue et al. (2015); Jun et al. (2015); Hojin et al. (2015)
8	Ishizuka and Miki (2015); Ig Mo et al. (2008); Teh et al. (2008); Samani et al. (2013); Furukawa et al. (2010); Pfab and Willemse (2015); Mujibiya (2015)
9	Kadowaki et al. (2007); Sato et al. (2009); Ariyakul and Nakamoto (2014); Hashimoto and Nakamoto (2015)
10	Matsukura et al. (2013); Yanagida et al. (2013)
11	Ranasinghe et al. (2012, 2015); Wade (2003)
12	Tasaka and Hamada (2012); Bazrafkan et al. (2015)
13	Dubois and Charpillet (2014); Dubois and Bresciani (2015); Kondyli et al. (2015)
14	Qiu et al. (2015); Srinivasan et al. (2010); Bo et al. (2014); Abdelnasser et al. (2015)
15	Elhoushi et al. (2014)
16	Trawicki et al. (2012); Giannoulis et al. (2015); Soda et al. (2013); Ishi et al. (2015)
17	Turan and Erzin (2016); Toda et al. (2012); Rahman et al. (2015); Alberth (2013); Mandal et al. (2009)
18	Hu et al. (2015); Nakayama et al. (2015)
19	Voelker et al. (2014); Craven et al. (2014)
20	Vaz et al. (2010); Zhexiang et al. (2014)
21	Minglei et al. (2014); Fonollosa et al. (2014)
22	Kea-Tiong et al. (2011); Seesaard et al. (2014)

movement of facial muscles. Detection of human behaviours as well as their sex, age or ethnicity is accomplished by the analysis of features through the spontaneous facial images with reasonably resolution so landmarks can be clearly labelled on human faces (Mavadati et al., 2013; Tasli et al., 2015). Tracking of mouth-shapes and lips movements provides visual speech recognition which helps vocal communication in noisy environment (Tasaka and Hamada, 2012). Eye-gaze tracking allows humans to communicate with computer through the tracking of pupil's position or pupil corneal reflection through examining visual images of the human eyes (Bazrafkan, Kar and Costache, 2015). Ambient lighting condition affects the image clarity seriously, thus the application is restricted.

Depth cameras and thermal cameras improve the privacy by capturing the contour of target body parts and is less affected by ambient lighting. Applications can be found in analysing human gait sequence by capturing the images for locomotion. Analysis of the gait sequences can identify each individual for multiple dwellers in an ambient space, and the trajectory of the centre of mass for each person through feature extraction from the depth images can be used to detect human falls as well (Dubois and Charpillet, 2014; Dubois and

Bresciani, 2015). Human posture detection can also utilise depth image sequences through extracting a skeleton model for further examination on body parts movements. Kondyli et al. (2015) demonstrated the postures of different drivers based on skeleton models to compare driving attitude. PIR (Passive InfraRed) technology provides a simpler method detecting human body based on body temperature but the detection resolution and accuracy is relatively low.

Leveraging the RF (Radio Frequency) signals surrounding the human body can also detect body parts movements. Active and passive Doppler radar technologies are commonly adopted to track body parts. Active Doppler radar technology normally requires customized hardware using frequencies such as UWB (Ultra Wide Band), ultrasound, or mm-waves to detect moving objects using the Doppler effect. Detection accuracy and resolution for active Doppler radar is high but it requires dedicated transmitters and receivers, where required frequencies may have potential interference with existing RF systems. The capability of radar to penetrate through walls allows detection of minor human movement from a distance, Qiu et al. (2015) reviewed how active Doppler radar applied from the outside of a building to detect human micro-motions such as respiration and heart beating for people living inside. Silent speech interface is an emerging research area where the Doppler effect based on ultrasound allows the detection of speech through the decoding of lip and mouth movements (Srinivasan, Raj and Ezzat, 2010). Passive Doppler radar utilises RF signals already existing in the environment as transmission signals and detects the variations of the received signal due to reflections from human body parts, thus the detection system set up is comparatively less complicated and the interference becomes minimal. The widespread use of WiFi technology at home enables the application of passive Doppler radar for hand gesture detection using WiFi frequency bands (i.e. 2.4GHz and 5GHz) as the radar frequencies (Bo, Woodbridge and Chetty, 2014). To further simplify the hardware requirement, Abdelnasser, Youssef and Harras (2015) demonstrated a gesture detection algorithm using the variation of RSSI (Received Signal Strength Indicator) of the WiFi signal due to the interference of human body parts, thus no extra hardware is needed but the detection distance was much shorter.

Wearable sensors enable an accurate detection of wearers' motions through a combination of traditional sensing elements such as accelerometers, gyroscopes, magnetometers, and barometers. Recognition of walking, running, cycling, or driving are achievable with reasonable accuracy (Elhoushi et al., 2014). Together with MEMS technology, wearable sensors are logical DUIs once they are well hidden in human bodys like embedding in smartwatches or clothing.

(2) Body Sounds

Body sound is another popular human output and can be classified as "speech" and "non-speech". Humans generate speech by pushing air from the lungs through the vocal folds, while non-speech sound is the result of the sound producing by various internal and external parts of the human body such as body parts movement, heart beat, breathing, drinking or swallowing, etc.

Capturing ambient sounds normally utilises a microphone to convert sound waves into electrical signals. A single microphone is capable of performing an accurate conversion when the speaker is within an effective pick-up distance under high SNR (signal to noise ratio) condition, thus the application for DUI is limited. Distributed microphone networks enabling ambient sound capturing without fixed pick-up spots allow speakers to travel within an open space in single or multiple rooms environment. Data fusion of distributed sound signals from different areas can then enhance automatic speech recognition by localisation of speakers and reduction of background noise (Trawicki et al., 2012; Giannoulis et al., 2015). A microphone array further enhances captured sound quality by putting multiple microphones in grid form to expand the coverage and enable the face orientation estimation of speakers (Soda et al., 2013; Ishi, Even and Hagita, 2015).

Miniaturised on-body sound capture devices enable the detection of both speech and non-speech body sound. Skin-attached piezoelectric sensors such as throat or non-audible murmur (NAM) microphones convert tissue vibrations into recognizable speech which falls into the emerging research field of "silent speech interface" (Turan and Erzin, 2016; Toda, Nakagiri and Shikano, 2012). Similar sensors attaching to different parts of the human body allows the detection of various body internal activities which translate into human output actions, examples are dietary monitoring through eating sounds, lungs condition monitoring through breathing sounds, human emotion monitoring through laughing and yawning sounds, etc. (Rahman et al., 2015). Miniaturisation (e.g. electronic tattoo) and the continuous supply of operating power (e.g. wireless power) are key factors making this interface successful as DUI for detecting human sound output (Alberth, 2013; Mandal, Turicchia and Sarpeshkar, 2009).

(3) Body Temperature

Human bodies in their living form generate heat by metabolism, muscle contraction, intake of food, and non-shivering thermogenesis (neonate only); whereas body heat is lost from the body through the processes of radiation, convection, conduction and evaporation (Campbell, 2011). Humans are homeothermic so they try to maintain a constant body temperature through physiological adjustments, but body temperature still varies dynamically due to human body conditions (e.g. health, emotions, environment, etc.). Capturing the human body temperature is often achieved through remote sensing based on an Infra-Red (IR) camera or on-body direct thermal sensing.

Thermal radiation from human bodies consists primarily of IR radiation according to Wien's law, which treats human body as a black-body radiator and the estimated wavelength of the emitted EM (Electromagnetic) wave falls into the IR region of the spectrum thus invisible to human eyes. Images showing the thermal maps of the human bodies are therefore captured by IR camera which is mentioned in section 4.2.2 that the data is used for detecting body parts movement. Recently IR images also enable facial recognition in dark environment by capturing thermal images of human faces to assist the recognition process by comparing details with normal facial images in database (Hu et al., 2015). Facial signatures reflecting body conditions due to the fluctuations in skin temperature are being remotely captured by many airports for mass screening of passengers for infection quarantine, e.g. to prevent SARS (Severe Acute Respiratory Syndrome) (Nakayama et al., 2015).

Personal micro-climate is the result of body heat convection where a layer of warm air is surrounding the human body, and the rising air becomes human thermal plume appearing above the head with air rising velocity proportional to the temperature difference between the human body and the surrounding air, therefore thermal plume can be used to detect the comfort level of the human body so as to control the ambient air-conditioning (Voelker, Maempel and Kornadt, 2014). Craven et al. (2014) demonstrated the using of Schlieren imaging to capture human thermal plume for an application of chemical trace detection which monitors and detects the air flow of a walking suspect in a security gate for carrying illegal chemicals.

Wearable thermal sensors capture body temperature by direct skin contact. Temperature sensing is a mature technology and miniaturisation becomes the major design criteria for attaching unnoticeable sensors to the human bodies, Vaz et al. (2010) proposed an RFID tag with long range wireless connection and low profile on-body temperature sensing. A bold attempt uses electronic capsule housing a self-powered temperature sensor for swallowing into human body, however, technical and psychological concerns are big challenges (Chi et al., 2014).

(4) Body Odour

Body odour is the result of the emission of various Volatile Organic Compounds (VOC) from the human body, and is normally carried by the warm-air current of a personal micro-climate to the outside world (see Secion 4.2.2). Research has found that some VOC are the reflection of certain diseases which change the human metabolic condition, thus the detection of VOC signature applies to health care monitoring (S. Li, 2009; Shirasu and Touhara, 2011).

Ambient capturing of human body odour is achieved through the air circulation in an open space, VOC are collected from the circulated air and detected by gas detection systems. Chemical sensors are used for detection of pre-defined VOC and Gas Chromatography (GC) together with mass spectrometry are applicable to generic chemical analysis of VOC based on mixture separation techniques. Shu, Liu and Fang (2014) proposed a GC system for biometrics using body odour as personal identity, and Fonollosa et al. (2014) used chemical sensors for activity recognition where activities of multiple dwellers can be estimated using classification of captured VOC in a living space.

Personal body odour detection is achieved by wearable detector such as eNose (electronic noise) which normally consists of chemical sensors with their electrical characteristics changed once the coated chemically sensitive materials (e.g. metal oxides, carbon nanotubes, etc.) are in contact with the VOC (Tang et al., 2011). Embedding the sensors in clothing is a good way to keep an effective personal VOC detection non-noticeable (Seesaard et al., 2014).

(5) Physiological Parameters

Physiological parameters are mostly presented as biosignals for monitoring human body functions, for examples the primary vital signs are body temperature, blood pressure, heart beat, breathing rate which can be captured by DUIs mentioned in the previous sections through indirect methods. In order to get an accurate measurement of all biosignals, direct biomedical examination is needed through common methods such as Electroencephalogram (EEG), ECG, EMG, Mechanomyogram (MMG), Electrooculography (EOG), Galvanic Skin Response (GSR) or EDA, etc. Measurement of physiological responses is essential for recognising human emotions which activate or deactivate the human autonomic nervous system (Kreibig, 2010). Active research in psychophysiology has been proposing effective measuring methods to identify different feelings (e.g. angry, sad, fear, happiness, etc.) under the umbrella of affective computing (Picard, 1997) and psychophysiology (Cacioppo, Tassinary and Berntson, 2007). Chapter 2 section 2.3 presents a detailed literature review on related disciplines.

4.3 Sixth Sense and Super Senses

Humans do possess more than five senses according to numerous research as briefly discussed in previous section 4.2.1, but there is no formal classification for ranking them as the sixth human sense. The fact that "sixth sense" has long been referred by the general public as paranormal phenomena could be one reason. Parapsychology has been an active research topic for decades exploring those paranormal activities and psychic abilities for human beings. Many institutions and organisations all over the world under the umbrella of Parapsychology or Extrasensory Perception (ESP) are getting involved with continuous publications of research papers and empirical reports gaining controversial results. This chapter will not comment or criticise any parapsychology area, however, the application of DUIs to enable what may be seen to be paranormal activities or psychic abilities for normal human being catches our attention. Extrasensory perception is the ability to use "extra" human senses to perceive things that are not normally achievable as an ordinary people, such as feeling someone far away or talk to a dead person. There are recent experiments reporting the fusion of sensors based on ubiquitous computing which enable humans with extra senses by delivering data from surrounding sensors to them when they walk by

(Dublon and Paradiso, 2014), and Mistry, Maes and Chang (2009) also proposed a "Sixth-Sense" wearable gesture interface device merging on-body computer and on-body sensors with cloud computing for augmented reality application which enables individual to collect whatever data from ubiquitous computing devices through hand gesture recognition. Ubiquitous computing, IoT and big data through cloud computing already provide immediate tools for data-fusion and sensor-fusion which allow humans to interact with the world easily, for example, humans can check the road traffic five blocks away with the estimated time to get there, or see the real-time image of a street in New York from London and locate a particular face, or estimate a 10-day weather forecast with high accuracy through computational intelligence and past history. Accessing all these complicated technologies naturally through DUIs can seamlessly merge humans with the fusion of data and sensors, and ultimately DUIs can turn on the so-called sixth sense through simulation. Table 4.2 shows some examples of applying DUIs for enabling normal human to gain common psychic abilities which are generally described as the sixth sense.

Supersenses or super senses, similar to the sixth sense, are also treated as supernatural behaviours among the general public, and the term "super senses" is sometimes associated with animal senses that are superior to the human senses in terms of sensitivity and functionality[5]. Super sense in this work refers to the extension of human senses which enhances temporal, spatial, and most importantly contextual senses. IoT is shaping the Internet into a global nervous system[6] [7], thus the growing number of ubiquitous sensors, based on context awareness technology, enables local and remote contextual sensing anywhere in the world when an Internet connection is reached. This huge IoT nervous system is then the sensory extension for each connected individual.

Context Awareness technology in Ubiquitous Computing not only provides a platform for mobile computing to be location sensitive, but also enables the mobile devices to be smart. Dey, Abowd and Salber (2001) defined context a decade ago as *"any information that characterises the situation of entities"* and laid down the groundwork for smart mobile computing devices that can accurately aware and astutely react based on the corresponding context

[5] http://news.nationalgeographic.com/news/2014/11/141105-mammal-evolution-vintana-fossil-science/

[6] https://www.theintelligenceofthings.com/article/the-internet-or-things-is-becoming-a-new-nervous-system/

[7] https://blogs.cornell.edu/info2040/2015/10/23/humanity-gaining-a-nervous-system-the-internet/

TABLE 4.2: Examples of applying DUIs for Extrasensory Perception

Extrasensory Perception		DUIs for human inputs	DUIs for human outputs	Remarks
Clairvoyance/ Necromancy	The alleged ability to communicate with people far away or even see and talk to dead people.	1. 3D display showing animated video of people from remote locations or dead person (Hyoung et al., 2013; Hong et al., 2011; Ishikawa and Saito, 2008; Miu-Ling et al., 2015). 2. Natural ambient sound broadcast (Cecchi et al., 2015). 3. Haptic jacket transfer the hugging feeling of the remote person (Teh et al., 2008; Samani et al., 2013).	1. Ambient sound capture with speech recognition (Trawicki et al., 2012; Giannoulis et al., 2015; Soda et al., 2013; Ishi et al., 2015). 2. Collect body temperature and hugging pressure and transfer to remote site (Teh et al., 2008; Samani et al., 2013)	Capturing of 3D images with facial and body parts details must be done when the subject person is still alive for a computer graphics to simulate real time body movement on a 3D display. Pre-defined questions and answers are also recorded in advance for real time interaction [http://theinstitute.ieee.org/technology-focus/technology-topic/3d-hologram-technology-will-make-it-possible-to-virtually-connect-with-people-after-theyre-gone]. An enhancement of communication can be achieved by recording the temperature or pressure for hugging so the person wearing a haptic jacket can feel the hugging from people far away or the dead people.
Clairaudience	The alleged ability to hear sound or speech that is not audible to normal humans.	Directional audio using parametric speaker array or body self-demodulation of ultrasound (Akahori et al., 2014; Woon-Seng et al., 2011; Sung-Eun et al., 2014; Kim et al., 2013; Betlehem et al., 2015)	Lip reading through visual image recognition to detect inaudible speech from a distance (Tasaka and Hamada, 2012; Bazrafkan et al., 2015)	Detection of speech from noisy environment or from a long distance can be achieved through facial feature recognition and the recognised speech is transferred to the subject listener.
Remote viewing	The alleged ability to see something far away through perception.	1. Smart eye-glasses can see remote images or video through wireless communication (Brusie et al., 2015), or 2. Wearable projector displays image on wearer's body (Rakkolainen et al., 2015).	1. Install "on-body interface" can connect with ubiquitous computing to select the source of images (Harrison and Faste, 2014), or 2. Speech recognition system to select the images sources (Trawicki et al., 2012; Giannoulis et al., 2015; Soda et al., 2013; Ishi et al., 2015; Turan and Erzin, 2016; Toda et al., 2012; Rahman et al., 2015; Alberth, 2013; Mandal et al., 2009).	Camera from remote site sends images to the subject person through the Internet, and this is already a common technology nowadays.
Precognition	The alleged ability to predict the future.	Directional audio using parametric speaker array or body self-demodulation of ultrasound (Akahori et al., 2014; Woon-Seng et al., 2011; Sung-Eun et al., 2014; Kim et al., 2013; Betlehem et al., 2015)	Activity recognition from tracking human locomotion to detect where the subject person is going (Dubois and Charpillet, 2014; Dubois and Bresciani, 2015; Kondyli et al., 2015; Elhoushi et al., 2014).	Example of informing a person about bad traffic condition or bad weather condition after a prediction of human behaviour through activity recognition using motion detection and localisation techniques. Probabilistic algorithm is used to choose the most probable result.
Telepathy	The alleged ability to communicate with other humans through their mind instead of normal sensory system.	1. Personalised sound interface using modulated ultrasonic vibration attaching to human body (Sung-Eun et al., 2014); Kim et al., 2013), or 2. Wearable tactile display for transferring special haptic codes from another party (Ishizuka and Miki, 2015).	Silent speech interface using on-body tissue vibration sensors to detect human speech (Turan and Erzin, 2016; Toda et al., 2012).	Communication between two parties far apart can be accomplished by collection speech from each person through silent speech interface, and the compressed and encoded speech is transferred through the Internet. Finally the speech is silently acquired by another party through personalised sound interface (ultrasound self-demodulation) or sensory substitution through tactile display.

information. Collection of past and present contexts provides cues for making immediate decisions (Rosa, Barbosa, Kich et al., 2015) and predicts future actions as well (Rosa, Barbosa and Ribeiro, 2016).

Emotion promotes behavioural and physiological responses by activating the autonomic nervous system (Kreibig, 2010), and at the same time the experience or emotional memory is encoded onto the neural circuits in the brain through the limbic system (LaBar and Cabeza, 2006). The famous "Little Albert Experiment" shows that once a particular emotional memory is consolidated in the brain, the emotional response becomes Conditioned Emotional Response (CER) which can be recalled by Conditioned Stimuli (CS) (Watson and Rayner, 2000). CS is the context of the emotional experience which is usually stimulated by an Unconditioned Stimuli (US). For examples, (1) a dog barking sound is the CS and a dog bite is the US in an emotional experience of "bitten by a dog", (2) a bicycle riding activity and a bad weather together are the CS and the falling on the ground is the US in a road accident happened in a raining day. Emotional Context Awareness (ECA) is possible to discover or "sense" the CS through recorded contexts with emotional tagging (Alam et al., 2011), and it can be applied to predict emotions based on machine learning and specific context prediction algorithms.

Context conditioning is an emerging research based on CER and CS/US, and researchers in this field normally focus on applications that detect or make extinct anxiety or fear (Kastner et al., 2016; Cagniard and Murphy, 2013; Kerkhof et al., 2011). Research on emotion prediction normally investigates the features extraction and classification methods on contexts stimulating emotion using machine learning algorithms (Ringeval et al., 2015; Fairhurst, Erbilek and C. Li, 2015), or focuses on the prediction algorithms under controlled contextual stimuli. However research on sensing the CS for emotional memories is not obvious. Sensing and extracting the ground-truth contextual datasets for training the prediction function is equally important. ECA together with context prediction is the sixth sense enabling mobile devices in ubiquitous computing to "have" emotions which allow humanised interaction to the users, e.g. it will advice the user to a session of physical exercise when he/she is currently sad and near a gymnasium since 80% of past emotional context shows that "workout" is followed by a happy emotion state.

4.4 Conclusions and Future Works

The number of users and the number of computers in the Ubiquitous Computing world have reached an unprecedented scale, and the associated interactions between multiple users and multiple computers at the same time become a profound issue requiring a novel HCI solution. A menu driven approach HCI requiring operational training will be ineffective to non-technical users, thus NUIs have been promoted as the future interface for Ubiquitous Computing, where users interact with computers based on intuition. Some NUIs, especially gesture NUIs are criticised as artificial naturality since they replace tangible interface devices such as mouse and keyboard with gestures in a menu driven approach. DUI, based on its unnoticeable nature, is a logical provision for natural HCI to intuitively interact with non-technical users without training. DUI can pave a new path for NUI to be more natural by hiding the interface from the users and target to interact with them through contents directly based on natural human inputs and outputs. The application of DUIs not only provides intuitive natural human interaction, but also extends human senses through ECA technology. Getting to know details about human inputs through stimulus to sensation to perception, and human outputs through the brain to body responses are necessary research required for successful DUIs in ubiquitous computing. Research has shown that there are human responses not controlled by the conscious mind, such as pulse rate, breathing rate, body temperature, or even certain facial and gesture expressions; and these responses are classified as behavioural and physiological responses promoted by human emotions. Emotional memory is first encoded to the neural circuits through an emotional event stimulated by conditioned and unconditioned stimuli. This chapter lays the groundwork for an ongoing research for discovering the "conditioned contextual stimuli" for "conditioned emotional responses" using the concept of artificial sixth sense. Implementing an artificial sixth sense system based on the IoT technologies required for building SH will be the next step to investigate the feasibility of developing a novel intelligent HCI for ubiquitous computing.

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Chapter 5

emotionWear

A multidisciplinary literature research, according to Chapter 2 section 2.4, enables a conceptual design of an artificial sixth sense system to be realised through an integration of contemporary technologies based mainly on the IoT concept. There may be various technologies that prevent this artificial sixth sense system from a practical implementation, but a response-stimulus synchronisation is definitely one of the major obstacles. In order to verify the hypothesis stated in Chapter 1 section 1.2 that a synchronisation technology is missing in the proposed artificial sixth sense system to identify the timing for capturing the physiological response promoted from an emotional perception, a novel emotion recognition framework, the *emotionWear*, was proposed and built.

emotionWear is a complete emotion recognition framework designed from scratch for the purpose of this research that includes all functional blocks from emotion elicitation, physiological response capture, wireless data collection and storage, as well as a data analysis platform. Emotion elicitation is the first step in an emotional response which is normally stimulated by sensory transduction and is orchestrated by the brain (see Chapter 2 section 2.3). Selecting the proper types of stimuli, the stimulation methods and the controlled environment are the most important criteria for eliciting a true emotion during an emotion recognition experiment. Capturing the concomitant physiological response after a true emotion elicitation is the next process which detects and measures the variations of the related biological signals associated with the response. Choosing the appropriate biosensors, the location of biological measurement and the timing to take the readings are the critical decisions for an accurate recording of an emotional response (see Chapter 4). Once the corresponding bio-signals are captured, a convenient and reliable method for collecting and storing the raw data for further analysis is the third necessary step in the framework (see Chapter 3). A wireless data collection method fits well for the proposed DUI concept such that the physiological signals can be intuitively collected and stored in a remote storage as raw data for further processing. Finally, the emotion recognition algorithm can be applied to analyse the raw data from remote storage to validate a true emotion elicitation based on the OR hypothesis, and predict the emotion states according to the ANS specificity (see Chapter 2 section 2.3).

The purpose of the *emotionWear* is to verify the proposed hypothesis that the response-stimulus synchronisation is a missing technology in an emotion recognition function which is core to a conceptual artificial sixth sense system. *emotionWear* provides a controlled platform which allows a bespoke emotion recognition methodology to be tested through an integration of appropriate technologies on a single platform. The novelty of *emotionWear* is that it empowers the synchronisation between stimuli, physiological responses and the situational contexts. The selection of the various technologies to realise the different functional blocks (i.e. emotion elicitation, physiological response capture, data collection and storage, and data analysis) is flexible and under controlled, thus, the addition of a synchronisation algorithm in emotion recognition is effortlessly achieved. The result of an experiment conducted using the *emotionWear* showed that the response-stimulus synchronisation definitely helped increase the emotion recognition accuracy through the validation of a true emotion elicitation (see Chapter 6 for details).

A complete emotion recognition platform that is commercially available with the flexibility of making modification freely is not obvious. There are individual consumable parts that can be purchased but they are lacking of the capability for design customisation especially on the core hardware and embedded firmware. For example, the bracelet sensing devices and the accompanying smartphone apps for emotion research from Empatica[1], and the dedicated hardware and software platforms for biomedical research distributed by iMotions[2]. Without considering their unreasonable high price, they are both limited in functionality for raw data manipulation or substitution for alternative technologies. Therefore, the current research designed and built the *emotionWear* from discrete components and off-the-shelf modules in order to gain all necessary control for the whole emotion recognition process.

This chapter illustrates the details of the *emotionWear* from the conception stage of the

[1]www.empatica.com
[2]www.imotions.com

system architecture including the layout of the functional blocks (section 5.1), the decisions and the related thought process behind the measurement methodologies for emotions (section 5.2), the selection and integration of the wearable sensors as DUI for physiological response capturing (section 5.3), the choice and application of stimuli for emotion elicitation (section 5.4), the methodology for wireless data collection of the raw signals from the biosensors using various IoT technologies (section 5.5), the application of iPython as the data analysis platform for emotion recognition based on various data manipulation tools (section 5.6), the design and conduction of an experiment using human subjects for testing the hypothesis (section 5.7), and finally a conclusion was made summarising the pros and cons of using the *emotionWear* in emotion recognition and how it can be applied in the proposed artificial sixth sense system for future expansion (section 5.8).

5.1 System Design

A system design initiated by the conception of the *emotionWear* is depicted in fig. 5.1. *emotionWear* consists of all necessary functional blocks for testing and analysing an emotion recognition process according to the previous description.

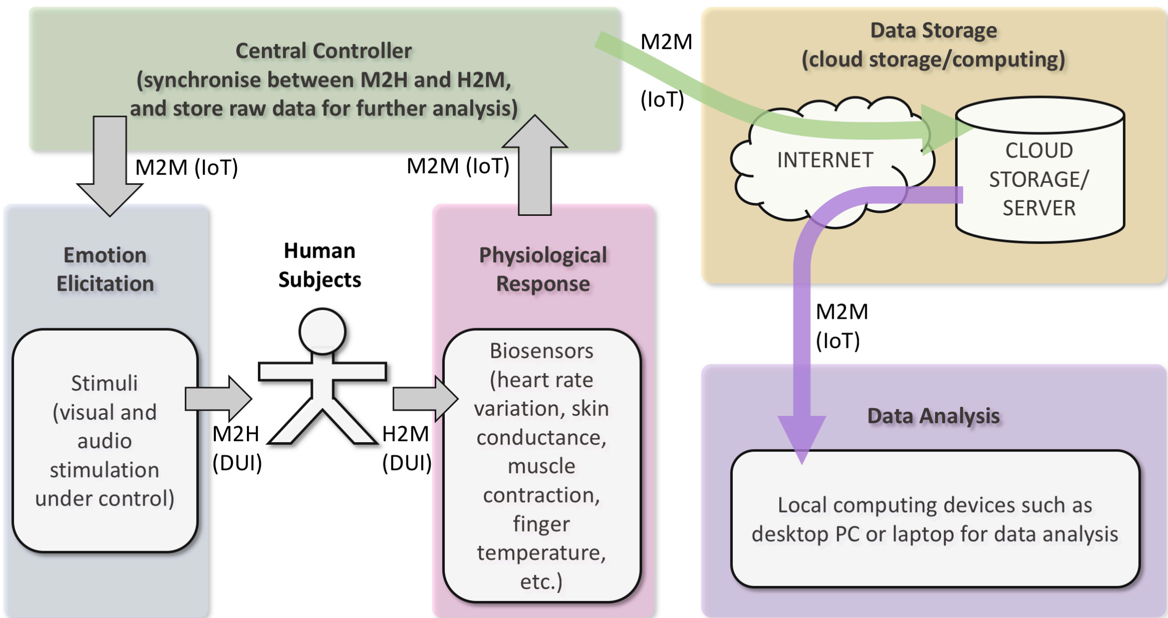

FIGURE 5.1: *emotionWear* System Architecture

An emotion elicitation block applies predefined stimuli (audiovisual contents in this study) to a human subject in a controlled environment avoiding other interference that affects the emotional perception, since human attention is easily distracted by other uncontrollable environmental contexts (Lang, 1995). Exposing audiovisual stimuli using monitor and speakers to the human subject under test in a private, quiet and darkened room is a traditional method for emotion elicitation. It requires a long time for reserving the facilities, setting up the environment and configuring the related equipments every time before conducting an experiment. Moreover, a traditional console type computer interface is not classified as DUI for intuitive interacting through M2H technologies with the human subjects (Hui and Sherratt, 2017). VR has become a viable M2H alternative as DUI for applying audiovisual contents to a subject using especially the VR headset which can isolate the wearers from the surrounding environment and focus substantively to the selected visual and auditory stimuli applicable to the experiment.

Physiological response detection and measurement allow the collection of an emotional response through the concomitant variations on body biological signals (see Chapter 2 section 2.3). Emotional physiological response is less subject to intentionally self-control as in emotional facial expression (Ekman, 1993; Beck, 2015), but the recognition of emotion states may require multiple variables extracted from various physiological signals such as heart rate variations through PPG, skin conductance fluctuations through EDA, degrees of muscle contraction through EMG and the subtle changes in fingertip temperature through SKT. In order to make the sensing glove more unnoticeable, PPG, EDA and SKT sensors were hidden inside a glove and the EMG sensor was attached to an arm-band wiring back to the glove with sufficient length allowing a reasonable arm movement. All sensors were connected to a wireless module, the *SPhere Wearable version 2 or SPW2* (Fafoutis et al., 2017), based on BLE connectivity transferring the collected physiological data to the central controller wirelessly. Therefore, unnoticeable wearable biosensors based on H2M technologies were realised that match the DUI concept for natural and intuitive human machine interactions.

A remote cloud storage for storing raw data of stimulation and response was suggested based on two main reasons. Firstly, it was due to the large amount of data collected per second that could easily fill up the relatively small local storage. Secondly, it allowed remote access of the data for off-site analysis during the experimental stage and during the future application stages with cloud computing services. There are many cloud storage and cloud computing services available and many of them provide free services as well. The "Google Drive" was chosen in this study since Google Cloud Platform[3] provides ample development facilities such as open Application Programming Interface (API) for remote data upload and download services through computing programming.

Response-stimulus synchronisation was achieved through a central controller coordinating the whole emotion recognition process from applying predefined stimuli for emotion elicitation, to capturing physiological response through wearable biosensors, to wirelessly collecting of biosensor signals through BLE, and uploading of raw data to the cloud storage through Wireless Local Area Network (WLAN). An Android smart phone was used as the central controller with a bespoke Java program installed for orchestrating the different functions to perform the necessary steps in sequence for an emotion recognition experiment. This smart phone was put inside a VR headset which enables the audiovisual stimuli to be applied to the wearer (i.e. the human subject) stimulating an emotional perception. Physiological response was detected and measured by the sensing glove where the biosignals were sampled and sent as notifications through a BLE subscription link between the smart phone and the *SPW2* module. The received raw data of the physiological variations was locally stored in the smart phone and later pushed to the Google cloud storage through the WLAN connection to the Internet via a local WLAN router.

The emotion recognition algorithm applies the hypotheses from previous psychophysiological research. Many researchers have hypothesised various emotion recognition algorithms based on psychology and physiology (Kreibig, 2010), and this study only focuses on using ANS specificity targetting on basic emotions proposed by Ekman (1992). iPython was chosen as the data analysis package for extracting the features from the raw data through various public libraries for data manipulation and analysis from the iPython community, for examples, using interpolation for filling up missing data due to lost in wireless packets, estimating signal trends to quantify signal variations, and comparing multivariate with ANS specificity, etc. This data analysis was done off-site after conducting the emotion recognition experiments with the *emotionWear* framework, and an Apple Macbook Pro laptop computer was used to download the data from cloud storage for performing the study. All predefined stimuli installed in the Android smart phone was also copied on this computer for a full analysis using response-stimulus synchronisation.

[3]https://cloud.google.com

Figure 5.2 illustrates the functional block diagram of the *emotionWear* according to the previous description using different contemporary technologies implementing the various functions depicted in the system architecture in fig. 5.1. Following this block diagram, the *emotionWear* was established for conducting the emotion recognition experiment based on the response-stimulus synchronisation concept.

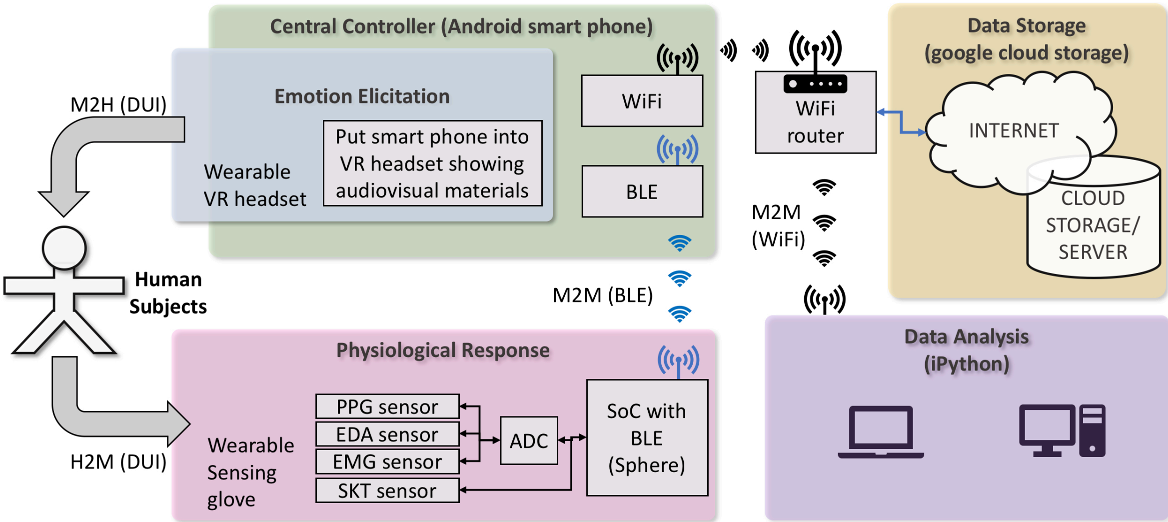

FIGURE 5.2: *emotionWear* Functional Block Diagram

emotionWear is part of the conceptual artificial sixth sense system, thus, the design concept also follows the seven requirements proposed in Chapter 3. The system design of *emotionWear* alone does not include all the ingredients that meet every requirement but the future expansion is reserved to reach the goal. Table 5.1 explains how the seven requirements for building smart homes govern the design of the *emotionWear* framework, most of the requirements have been met by choosing the appropriate technologies during the implementation of hardware and software.

The following sections in this chapter present in details the integration of each individual function into a complete framework including the choosing of hardware components and solutions, the implementation process including the encountering and solving of unexpected problems, the conduction of the experiment using the *emotionWear* including the protocol design and the ethical clearance procedures, the analysis of the raw data including the selection and implementation of data analytics and formula being used, and finally how the interpretation of the result of the experiment was turned into a research paper published in an academic journal.

TABLE 5.1: *emotionWear* and the seven requirements for building smart homes (refers to Chapter 3 for a detailed description of the requirements)

Requirements	Design guidelines for building *emotionWear*
Heterogeneity	A service centralised architecture or SCA was implemented on the Android smartphone platform which collected sensor data from a gateway. The current gateway was implemented using the *SPW2* module which converted wired-bus (Inter-Integrated Circuit (I2C) and Serial Peripheral Interface (SPI) ,etc.) protocols to BLE. One gateway was used for the current simple architecture but it would be straight forward to expand the number of gateways in order to access sensor or actuator using different protocols (e.g. Zigbee or Z-Wave edge devices). Additional gateways could be connected to the central server through BLE or WLAN since these were the two wireless protocols installed in the Android smartphone.
Self configurable	A star network topology was adopted for the initial design stage due to its simple architecture, and the adding or removing of new sensor was taken care through detection of received data based on programming algorithm (software engineering). The Java application running on the smartphone could recognise the data format received from the BLE channel to decide what sensors were correctly installed and used for the current configuration. BLE mesh protocol can be upgraded through the installation of a mesh network stack on the Android smartphone or adding a mesh proxy server in between the Android and the mesh network when the architecture becomes bigger and complicated.
Extensibility	The Java program on the Android phone could be upgraded over the air (OTA) through the Google Play service where new features including new stimuli for emotion induction were downloaded from a remote server to the internal flash memory of the Android phone. *SPW2* would be enhanced to be OTA upgradable in the near future. Therefore, a complete software upgrade system could be realised to improve the extensibility of the whole system.
Context awareness	Emotional context awareness was the major design goal for the *emotionWear* framework. Collection of physiological signals was combined with time stamps to allow context awareness algorithm for making further intelligent decisions or actions. Environmental context such as the background sound during the emotion recognition experiment was also recorded to increase the quality of the contexts. The context awareness algorithm was done on remote server for the initial stage but it could be moved to local server for real time control.
Usability	Except the installation of the wearable sensor glove to the user which required a third person due to the simple assembly of the prototype, the operation of the whole framework was designed to be as intuitive as possible. Instructions were displayed on the screen in front of the participants through the smartphone installed inside the VR headset, participants selected the correct stimuli and started the experiment all by themselves. Stimuli applied to them, physiological data collected from wireless channels, data was time stamped and uploaded to the cloud autonomously. A future upgrade on usability would be possible by detecting the eyelids closure to replace the pressing of a physical button on the VR headset.
Security & privacy protection	All data collected were unidentifiable and the files containing the data were password encrypted on firewall protected server. For future application, biometrics could be applied to individual artificial sixth sense server such that only authorised person or third parties could get assess to specific information.
Intelligence	*emotionWear* provided a pattern matching algorithm to enhance the physiological responses to emotional context awareness. With the extensibility quality of the system, various computational statistics methodologies could be installed to increase the accuracy of emotion recognition.

5.2 Measurement of emotions

The measurement methods for emotional responses are as debatable as the definition of emotion itself (James, 1884; Deigh, 2014; Beck, 2015). Before defining the methods for eliciting emotions and measuring the concomitant responses, the question about *"What to measure"* had to be answered first. There are many words in English, as well as in other languages, refer semantically to emotions. A formal study by Oatley (1989) has showed that 590 emotion related English words can be grouped into five basic emotion modes, however, most of them cannot be scientifically studied (Gendron, 2010). Emotions, emotion states, feelings, affects, moods, and stresses are common areas of study for emotion in psychology and psychophysiology during the past decades. Research on stress usually refers to clinical applications and health care, and is based on the hypothesis of distress and eustress proposed by Selye (1976). Lazarus (1993) has later concluded that stress is a subset of emotions since all related theories can be applied to both. Moods are emotional behaviours that last for a long period of time and the study focus is normally targetted to the monitoring of individual enduring emotions (Beedie, Terry and Lane, 2005). Affects are usually treated as emotions, but a new branch of study called Affective Computing was proposed by Picard investigating how computer could *"have emotion"* simulating and understanding human emotional behaviours (Picard, 1997). Feelings, similar in semantics as affects, is a subjective aspect of emotions but still cannot be scientifically defined (Munezero et al., 2014; LeDoux, 2015). Emotions seem to be an umbrella term referring to human or animal emotional behaviours due to the exposure to external or internal contextual stimulations, and emotion states as defined by Siemer (2009) are the emotions where an object is targetted (see also Chapter 2 section 2.3.3). The present research is, therefore, only focus on using emotion states to study emotion since they are empirically proven using scientific methodologies by numerous researchers (Kreibig, 2010). The terms *emotion state* and *emotional state* are assumed to have same meaning and are used interchangeably throughout the whole thesis.

The classification of emotions became the next critical decision in measuring emotional responses. After many years of debate, discrete and dimensional models are now the two major classification methods for emotion. A dimensional model is normally built on two basic dimensions: *Valence* ranging from positive (or good situation such as happiness) to negative (or bad situation such as sadness), and *Arousal* varying from high to low in the scale of wakefulness. Recently, there are new hypotheses proposing additional dimensions but the two dimensional model is still having a dominant position in emotion research (Schlosberg, 1954; Posner, Russell and Peterson, 2005; Fontaine et al., 2007; Yik, Russell and Steiger, 2011; Wyczesany and Ligeza, 2015). Discrete emotion model relies on the theories that humans have some natural kind of behavioural reactions to the changing world, and those emotional behaviours consist of some basic processes organised by the human brains (Barrett, 1998; Barrett, Gendron and Huang, 2009). According to Barrett, basic emotion and discrete emotion are considered as the same in the academic field since they refer to the basic instincts of animals including human beings. Although the argument between the two perspectives on classification models has never ended, many researchers believe that the dimensional model is complementary to the discrete model in the understanding of emotions (Plutchik, 2001; Hamann, 2012; Pelegrín-Borondo et al., 2015). Both models are used in empirical research studying emotion, and there are subtle differences in choosing the classification methods according to the type of investigation on emotional behaviour (E. Harmon-Jones, C. Harmon-Jones and Summerell, 2017).

Basic discrete emotions, such as anger, fear, disgust, sadness and happiness, are used in the present research due to three reasons. First, numerous references are available from previous empirical studies for emotional physiological research using basic discrete emotions and the ANS specificity such that the outcomes from the *emotionWear* framework can be easily compared with previous results (Mauss and Robinson, 2009; Kreibig, 2010). Secondly, the dimensional model utilises a continuous scale to define emotions where there are uncertainty added in the result interpretation since human subjective feelings are not precise enough to be classified on a non-discrete scale. Finally, despite the controversy, the postulation of five basic emotions (i.e. anger, fear, disgust, sadness and happiness) is having high level of agreement among scientists who are studying emotion (Ekman, 2016). Therefore, discrete model based on the five basic emotion states mentioned above was chosen in the *emotionWear* framework for emotion recognition through a physiological measurement.

5.3 Wearable Sensors

The design of a wireless sensing glove not only empowered a relatively accurate physiological measurement of emotional responses, but also fulfilled the requirement of the DUI concept for unnoticeable HCI (see Chapter 2 section 2.3, and Chapter 4). All sensors were embedded inside the glove and arm-band with direct skin contact for a reliable and continuous bio-signal measurements, data was transferred wirelessly through BLE to the Android smartphone which also enabled and disabled the communication link according to a preset sequence. Therefore, the physiological response detections could be synchronised with the application of emotional stimulations under the control of a computer program.

The physiological signals for emotion recognition in the present study were chosen based on previous psychophysiological research. According to section 5.2, the current study only focused on using the five generally agreed emotional labels to support the groundwork for building the *emotionWear* as a proof of concept verifying the proposed hypothesis listed in Chapter 1 section 1.2. Each label refers to an emotion state reflecting a particular behavioural response associated with a pattern of physiological variations such as the various degrees of cardiac acceleration and deceleration that cause changes in heart rate, the pulsatile secretion of sweat that causes fluctuation on skin conduction, and the triggering of peripheral vasoconstriction that causes a decrement in fingertip temperature (see Chapter 2 section 2.3). A summary from Kreibig (2010) provided a hint in choosing the biological signals from previous psychophysiological research that needed to be studied for detecting each emotion state mentioned above. The following context describes in details the whole selection process.

Figure 5.3 depicts an extraction of the physiological signals that have been verified as concomitant to the five basic emotion states from Kreibig's summary on previous studies of psychophysiological responses from researchers all over the world. Only those signals related to the five basic emotions were extracted, and all symbols were reused from the original article, for examples, the different formats of the arrows (e.g. ↑, ↓, ↑↓, etc.) representing the various variations of the corresponding bio-signals, as well as the frequency of occurrences (e.g. (↑), ↓--, etc.).

Removing those features in fig. 5.3 that show inconsistent results among previous empirical research such as having both increment and decrement signal trends for the same

Features	Anger	Disgust Contamination	Disgust Multilation	Fear	Sadness Crying	Sadness Noncrying	Sadness Anticipatory	Sadness Acute	Happiness
Cardiovascular									
HR	↑	↑--	↓	↑	↑	↓	↑	↑--	↑
HRV	↓	↑	--	↓	--	↓	(↓)		--
LF				(--)					
LF/HF			(↓)						
PWA				(↑)					
TWA	↓		(↑)	(↓)					
LVET	↓	(↓)	(↓)	↓			↓↑		(--)
HI	↑			(↑)					
PEP	↓	(↓)	(↓)	↓			↓↑	↑	(↑)
SV	↓↑	↓	(--)	↓			↓--		(--)
CO	↓↑	(↓)	(↓)	↑			↑--		(--)
SBP	↑	↑	↑	↑			↑	(↓)	↑
DBP	↑	↑	↑	↑			↑	↓--	↑
MAP		↑	↑	↑				↓--	↑
TPR	↑	↑	(--)	↓			↑		(↑)
FPA	↓	↓	↓	↓	↓	↓	(↑)	↓	↓↑
FPTT	↓	↓↑	↓↑	↓			(↓)	↑	↑
EPTT		↓↑	↓↑	↓				↑	↑
FT	↓	↓↑	↓↑	↓	↓	↓	↓↑	↓	↑
HT	↓↑	(↓)	(↓)						
Electrodermal									
SCR	↑	↑	↑	↑				↓	
nSRR	↑	↑	↑	↑	↑	↓	↑	↑--	↑
SCL	↑	↑	↑	↑	↑	↓	↑	↓	↑--
Respiratory									
RR	↑	↑	↑	↑	↑	↑	↓↑	↓↑	↑
Ti	(↓)	↓	--	↓--				(↓)	↓
Te	(↓)	↑	--	↓				(↓)	↓
Pi	(↑)			(↑)					(↓)
Pe								(↓)	
Ti/Ttot		(↓)	--	(↑)					
Vt	↓↑	↓	(↓)	↓↑	↓	↑	↓↑	↓	↓↑
Vi/Ti		(↓)	--						(↑)
V(rhyth)		(↑)	--				(↑)		(--)
V(vol)	(↑)	(↑)	--	↑					(↓)
sighing									
Ros	(↑)	(↑)	--						(↑)
pCO2				↓				↑	

FIGURE 5.3: Table showing features extracted from Kreibig's meta-analysis on ANS specificity studies for the five basic emotions

emotion, or not having empirical data on the subject emotion states, or only a few researchers recorded the observations, two features were ultimately left for the current study (reveals in table 5.4): heart rate (HR) and the electrodermal response (SCR/SCL). These two features were used as the main indicators for emotion recognition on the *emotionWear* framework.

Cardiovascular features are the most popular bio-signals among all that have been used for psychophysiological research according to Kreibig's summary. A lot of the cardiovascular features can be derived from a raw heart rate (or HR), such as Heart Rate Variability (HRV), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), etc. (Jeyhani et al., 2015; Shaffer and Ginsberg, 2017). Both SNS and PSNS branches of the ANS innervate the heart during emotional perception, and at the same time normal daily activities also activate the pace maker cells, HR is therefore constantly changing to cope with the dynamic environment inside and outside of the human bodies (see Chapter 2 section 2.3.3). As a result, HR alone may not be suitable to act as a sole indicator for emotion recognition. Thus, an additional feature in the cardiovascular system that is affected only by either SNS or

Features	Anger	Disgust Contamination	Disgust Multilation	Fear	Sadness Crying	Sadness Noncrying	Sadness Anticipatory	Sadness Acute	Happiness
Cardiovascular									
HR	↑	↑--	↓	↑	↑	↓	↑	↑--	↑
HRV	↓	↑	--	↓	--	↓	(↓)		--
LF				(--)					
LF/HF			(↓)						
PWA				(↑)					
TWA	↓		(↑)	(↓)					
LVET	↓	(↓)	(↓)	↓			↓↑		(--)
HI	↑			(↑)					
PEP	↓	(↓)	(↓)	↓			↓↑	↑	(↑)
SV	↓↑	↓	(--)	↓			↓--		(--)
CO	↓↑	(↓)	(↓)	↑			↑--		(--)
SBP	↑	↑	↑	↑			↑	(↓)	↑
DBP	↑	↑	↑	↑			↑	↓--	↑
MAP		↑	↑	↑				↓--	↑
TPR	↑	↑	(--)	↓			↑		(↑)
FPA	↓	↓	↓	↓	↓	↓	(↑)	↓	↓↑
FPTT	↓	↓↑	↓↑	↓			(↓)	↑	↑
EPTT		↓↑	↓↑	↓				↑	↑
FT	↓	↓↑	↓↑	↓	↓	↓	↓↑	↓	↑
HT	↓↑	(↓)	(↓)						
Electrodermal									
SCR	↑	↑	↑	↑				↓	
nSRR	↑	↑	↑	↑	↑	↓	↑	↑--	↑
SCL	↑	↑	↑	↑	↑	↓	↑	↓	↑--
Respiratory									
RR	↑	↑	↑	↑	↑	↑	↓↑	↓↑	↑
Ti	(↓)	↓	--	↓--				(↓)	↓
Te	(↓)	↑	--	↓				(↓)	↓
Pi	(↑)			(↑)					(↓)
Pe								(↓)	
Ti/Ttot		(↓)	--	(↑)					
Vt	↓↑	↓	(↓)	↓↑	↓	↑	↓↑	↓	↓↑
Vi/Ti		(↓)	--						(↑)
V(rhyth)		(↑)	--				(↑)		(--)
V(vol)	(↑)	(↑)	--	↑					(↓)
sighing									
Ros	(↑)	(↑)	--						(↑)
pCO2				↓				↑	

FIGURE 5.4: ANS specificity features for current study

PSNS during an emotional behaviour may assist the emotion recognition through psychophysiological measurements. One of them is the fingertip temperature which describes the momentary surface blood vessel constriction causing the subtle temperature drops in acral skin during an emotional promotion. It is relatively slow in variations, limited in application due to the interference with environmental temperature, and is affected by the both the SNS and PSNS branches (Freedman, 1991; Kistler, Mariauzouls and Berlepsch, 1998; Lin et al., 2011). EDA measures the skin conductance variation due to the pulsatile discharge of human sweat glands innervated solely by the SNS branch of the ANS during emotional processing. However, EDA can also be influenced by other activities (see Chapter 2 section 2.3) as well as the hypothesis of non-specific responses (Cacioppo, Tassinary and Berntson, 2007), it is not a clean signal for emotion recognition even it is not contaminated by the parasympathetic activities. Therefore, fingertip temperature (SKT) may act as an assistant indicator for emotional behaviour monitoring that work simultaneously with both HR and EDA. Although inconsistent performance was observed in previous studies, it was still included in the present research as a supporting feature for emotion recognition.

Respiratory related features are hypothesised as a good indication of emotional behaviours (Bloch, Lemeignan and Aguilera-T, 1991; Boiten, Frijda and Wientjes, 1994). However, a research on contemporary technologies for implementing a DUI interface detecting breathing rate does not provide an unnoticeable and effective way for intuitive human interaction, but there are indirect methods deriving the feature from ECG or PPG bio-signals (H. Kim, J.-Y. Kim and Im, 2016; Touw et al., 2017). In addition to the inconsistent results from previous studies illustrated in fig. 5.3, respiratory measurements were confirmed not to be included in the present experiment.

The inclusion of EMG sensor detecting the muscle contraction was the result from a literature review on body action coding by Huis in 't Veld, Van Boxtel and Gelder (2014). Other than the general idea of facial expression which drives the muscles activating the different parts of the human facial tissues, there are scientific research investigating the muscle contraction for other parts of the human peripherals. However, the references for a consistent emotional muscle contraction is not obvious. Since it is an easy upgrade of the *emotionWear* to include other sensors to enhance the number of features for emotion recognition, an off-the-shelf EMG sensor was added onto the framework.

Pupil size has long been treated as an alternative indicator for emotional response where pupil dilation reflects the concomitant response promoted by an emotional arousal (Bradley et al., 2008). Measuring the pupil size can be achieved by a normal visual spectrum camera focusing on the eyes, capturing the images, extracting and measuring the pupil sizes through image processing algorithm. Pupil dilation is also part of the orienting response so it is helpful in locating the OR event during emotion (C. A. Wang and Munoz, 2015). However, Oliva and Anikin (2018) have pointed out that pupil size fluctuations are affected by cognitive and other non-emotional perceptual tasks. Inconsistent pupil dilation has been found on pleasant and unpleasant stimuli, so it is hard to define whether a larger dilation reflects positive or negative emotion. Moreover, light reflex causes fluctuations on pupil size that would require special compensation algorithm with light intensity of the corresponding visual stimulus (Partala and Surakka, 2003). Ultimately, two main reasons that have disapproved the inclusion of pupil size sensor in the current study: (1) cross reference between pupil sizes with basic emotion states is not obvious, and (2) putting a camera inside the VR headset is not a straight forward approach due to the restricted time for the current study.

The selection of wearable sensors was finally confirmed on the four biosensors listed below, and the details including the specifications of all these sensors can be found from Appendix A:

a) PPG: A photoplethysmographic sensor was used to detect the fluctuation of light reflecting from surface blood vessels for measuring heart rate and extracting raw signal of the dynamic changing pulses. ECG is a more accurate method for measuring HR but a multiple electrode measurement is normally required, however, PPG has been chosen since it is closer to the DUI concept and recent study has shown that the accuracy for PPG is compatible for most applications (Jeyhani et al., 2015). The PPG sensor was embedded in the sensing glove directly touching the thenar muscles of the palm since this is one of the most sensitive areas for PPG detection. Due to the strong pulse signal on this area, a common off-the-shelf PPG sensor was acquired for the measurements, where the photo-sensor detected the variation on light reflection and passed through filters and low noise amplifiers extracting the level of reflection as an analogue signal. A dedicated Analogue to Digital Conversion (ADC) chip was installed inside the sensing glove to convert analogue signals to digital for wireless communication through the BLE protocol.

b) EDA: An electrodermal activity sensor was used to detect the galvanic skin conductance with two electrodes measuring the conductance between two areas of the skin. This sensor was also embedded in the sensing glove with the electrodes touching the thenar muscles of the palm where a strong conductance measurement could be obtained. A common off-the-shelf EDA or Galvanic Skin Response (GSR) sensor was acquired for this purpose where the measured conductance through the two electrodes was filtered, amplified and converted to a digital value using the embedded ADC chip mentioned above.

c) SKT: A thermo-sensor was used to detect the temperature fluctuation at the fingertip. High accuracy temperature sensing at 0.1°C was chosen in order to capture the subtle thermo variation in a range of a couple degree Celsius, digital output with built-in thermo-compensation was required to prevent the cable loss before ADC processing in the *SPW2* module. The final design utilised the I2C bus for linking the thermo-sensor with the *SPW2* module to prevent signal degradation through analogue signal transmission.

d) EMG: A muscle contraction sensor is used to measure the electrical activity produced for the activation of a skeletal muscle contraction. Special attention was paid on the activation of skeletal muscle during emotional promotion. There are many empirical evidence showing the facial muscle contraction contributing the different facial expression (Ekman, 1993), and the same principle applies to skeletal muscles in other parts of the body which is the main research topic of the body action code (Huis in 't Veld, Van Boxtel and Gelder, 2014; Huis In 't Veld, Van Boxtel and Gelder, 2014). A three electrodes EMG sensor module was acquired to be placed on the biceps and triceps area of an arm where the electrical potential activating the muscle contraction was monitored through the cascading of noise filtering amplifiers. The measured electrical potential was fed directly to the ADC port of the *SPW2* module to pick up the bio-signals. Due to the relatively short distance between the arm band and the sensing glove, a long enough wire allowing a reasonable arm movement was used to transfer the analogue muscle contraction activation potential to the *SPW2* module.

e) Sensing Glove: The sensing glove consists of a thumb and wrist support brace that was purchased online for holding the PPG and EDA sensors which contacted directly to the thenar muscles of a palm firmly using the elastic band that was adjustable for fitting different hand sizes, the SKT sensor was extended to the fingertip through wires connecting back to the *SPW2* module. A longer cable collected EMG signal from the arm band which attached the EMG sensor to the biceps or triceps area. Figure 5.5 depicts the block diagram of the sensing glove and fig. 5.6 shows the structure of the sensing glove with all sensors attached.

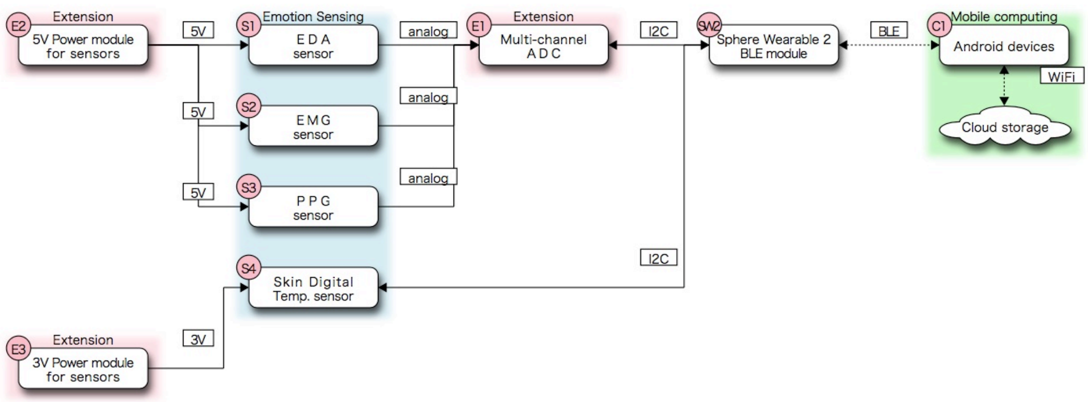

FIGURE 5.5: Sensing Glove Block Diagram

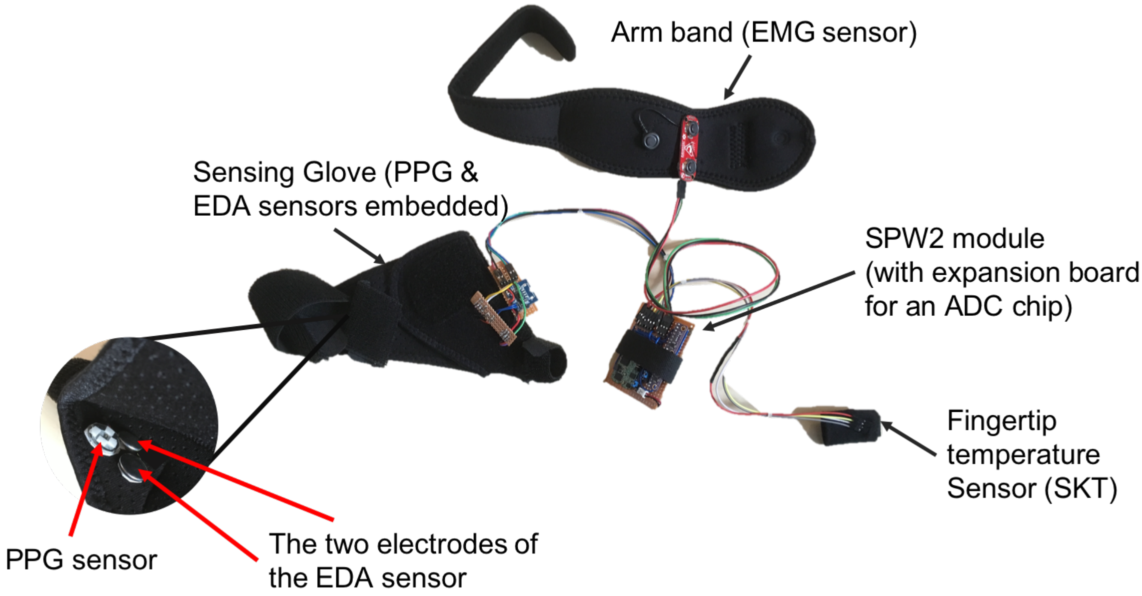

FIGURE 5.6: Sensing glove assembly constructed for this research

5.4 Emotion Elicitation

Audiovisual stimuli with emotion rating were chosen as the stimulation medium for emotion elicitation in the present study, and this selection was based on the literature survey which showed that audiovisual materials were the most popular methodology for studying emotion from previous psychophysiological research (Amodio, Zinner and E. Harmon-Jones, 2007; Kreibig, 2010). Applying these audiovisual context to the human subjects during the experiments was based on a VR headset which could easily capture the attention of a subject under test by limited isolation. Both still pictures from IAPS (Lang and Bradley, 2007; Lang, Bradley and Cuthbert, 2008) and commercial film clips identified by previous researchers (Gross and Levenson, 1995; Schaefer et al., 2010) were stored on the Android smartphone which was out inside the VR headset as a media player. The human subjects under test were presumably isolated from the environment and exposed to the controlled stimuli through the video and audio outputs of the Android smartphone when their physiological responses were collected using the sensing glove mentioned in the previous section (section 5.3). A controlled environment with predefined stimuli applying to elicit emotion was established by using an Android smartphone, the synchronisation between the application of stimuli and the physiological measurement through the wearable sensors was also achieved based on the bespoke computer program running on the smartphone.

There are various empirically proven methodologies for emotion elicitation from previous psychophysiological research (Stemmler, 2003; Coan and Allen, 2007). A literature survey shows that emotion elicitation can be roughly classified into self induction and external induction methods (Rein, Atkinson and McCraty, 1995; Zhuang et al., 2018). Self-induced emotions rely on recalling emotional episodes using Autobiographical Emotion Memory Tasks (AEMTs) which help promote the concomitant physiological responses through the influence of the human brains (Mills and D'Mello, 2014). Examples are found in *Acting Emotion* (Bloch, 1993; Konijn, 2010) where actors can perform emotional behaviours by drawing from their personal experiences. However, extensive training is required for experimenters such as professional actors before conducting a controlled emotion elicitation for an effective scientific study. Moreover, memory recall is usually not accurate and is subject to vulnerability of misinformation (Van Damme et al., 2016; Kaplan et al., 2016). External emotion induction may be more versatile and it can apply to predefined emotional stimuli, as well as a controlled human to human emotional interactions. Social psychological induction provides a real time face to face emotional interactions between the investigators and the human subjects, and this method is treated as a better method for inducing anger emotion since it mimic a real emotional situation (Amodio, Zinner and E. Harmon-Jones, 2007). However, similar to *Acting Emotion*, training is required to prepare the investigators to act like professional actors and this may take a long time to prepare. Predefined stimuli usually apply to stimulate the human sensory systems through the basic senses such as visual, auditory, olfactory, gustatory and tactile senses (see Chapter 4). Audiovisual context is the most popular stimulation media among all types of predefined stimuli for external induction of emotion according to Kreibig's summary, therefore, the current study has also adopted the audio and visual stimulation materials with reference emotional rating for conducting the emotion recognition experiment. Figure 5.7 depicts the emotion elicitation stimulus selection criterion.

Focusing on audiovisual stimuli revealed three common types of stimulation materials: audio only such as voice or music, still pictures without auditory content, and normal video with both visual and auditory contents. Audio such as emotional music is a common induction method but the emotional perception for the same piece of music can be quite different culturally for different groups of people (Scherer, 2004; Argstatter, 2016; Omigie, 2016). Moreover, there is no standard emotional rating for selected music libraries available

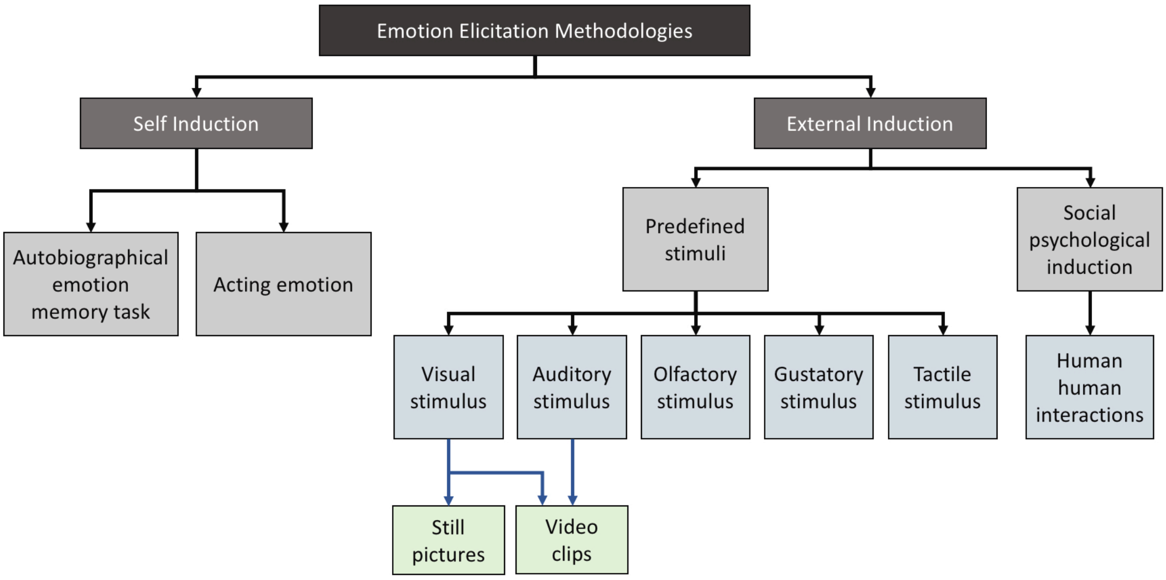

FIGURE 5.7: Emotion Elicitation Methodologies Analysis

as a reference for comparison in scientific study. Emotional still pictures enable the stimulation of the human visual sense only which is treated as relatively simpler in emotional response analysis (Lang and Bradley, 2007), and video clips provide a simulated authentic emotional experience which is more generalized to a real-life setting (Gross and Levenson, 1995). However, recent comparison studies show that the emotion elicitation effects for both methods are similar (Uhrig et al., 2016). Therefore, a collection of still pictures from International Affective Picture System (IAPS) (Lang and Bradley, 2007) and a list of short film clips from Schaefer et al. (2010) were chosen in the present research since both of them were having numerous references available for third-party study using same sets of emotional stimuli.

IAPS from the University of Florida provides a standard library of 1195 still pictures for emotion research, each picture was reviewed with emotional rating according to emotional valence and arousal. The IAPS system chooses to use a low to high scale on valence instead of negative and positive rating, where a low corresponds to a negative rating. Ten pictures having the highest rating and another ten picture from the lowest rating on the reference valence were chosen in the current study to get a high contrast between two emotional groups of still image stimulus, table 5.2 shows the chosen pictures from the IAPS database with their corresponding rating on valence and arousal. Similarly, short film clips from Schaefer's list were selected according to the types of perceived emotion and their associated rating is shown in table 5.3. Some of Schaefer's selections were also studied by Gross where same film clips applied to induce similar emotions (Gross and Levenson, 1995), but their list was not as complete as Schaefer's database.

TABLE 5.2: Selected IAPS pictures with reference valence and arousal ratings

Category	**IAPS reference number**	**Valence**	**Arousal**
Puppies	1710	8.34	5.41
Bunnies	1750	8.28	4.1
Beach	5830	8.22	5.71
Kitten	1460	8.1	4.31
Baby	2050	8.2	4.57
Seal	1440	8.19	4.61
Baby	2040	8.17	4.64
Baby	2070	8.17	4.51
Skier	8190	8.1	6.28
Babies	2080	8.09	4.7
BurnVictim	3053	1.31	6.91
BurnVictim	3102	1.4	6.58
Mutilation	3000	1.45	7.26
Mutilation	3064	1.45	6.41
BabyTumor	3170	1.46	7.21
Mutilation	3080	1.48	7.22
Mutilation	3063	1.49	6.35
Soldier	9410	1.51	7.07
Mutilation	3131	1.51	6.61
Accident	3015	1.52	5.9

TABLE 5.3: Selected short film clips from Schaefer with reference grouping and arousal ratings (the convention of the film clip names follows the original paper from Schaefer where multiple clips from the same film are indicated by different numbers bracketed at the end of the name, e.g. [1], [2], [3], etc.)

Category	**Film Clips (Names of Film Clips refer to Schaefer et al. (2010))**	**Arousal rating**
Happiness/Joy	(H1) Something About Mary [2]	3.84
	(H2) A fish called Wanda	4.04
	(H3) When Harry met Sally	4.67
Anger	(A1) Schindler's list [2]	5.13
	(A2) Sleepers	5.63
	(A3) Leaving Las Vegas	5.00
Fear	(F1) The Blair Witch Project	4.95
	(F2) The Shining	5.11
	(F3) Misery	6.12
Disgust	(D1) Trainspotting [2]	4.84
	(D2) Seven [3]	4.24
	(D3) Hellraiser	3.93
Sadness	(S1) City of angels	5.15
	(S2) Dangerous mind	5.25
	(S3) Philadelphia	5.24

All the chosen IAPS pictures, selected short film clips, and two longer version video files were stored in the Android smartphone. During the experiment, the investigator asked several questions of the human subjects and chose the appropriate types of audiovisual stimuli accordingly. For examples, subjects who afraid of horror movie would not see those film clips in the fear category, and subjects who were apotemnophobia would not be exposed to the pictures showing amputation or mutilation. The timing of when the audiovisual contents were exposed and the gaps between exposure were controlled by the program running in the smartphone, at the same time the start and stop commands for taking the physiological responses were also issued which then empowered the response-stimulus synchronisation process.

Both the IAPS still pictures and the emotional film clips were encoded into H.264/MPEG-4 files to make it consistent for applying to the participants during emotion elicitation. The media file format (H.264 encoding in a mp4 container, and will be referred to as MP4 in this thesis) is a recommended video encoding method for the Android operating system[4] and an encoder from the open source project Handbrake[5] was used to convert all media files into the required format at 30 frame per second (fps). The still IAPS pictures were compiled into a MP4 video allowing the same tool on the Android smartphone to use it for the emotion induction process together with other film clips. iMovie, an application included in the Apple OSX running on an MacBook Pro, was used to edit the IAPS film clip. The composition of the IAPS film clip is illustrated in fig. 5.8. All MP4 media files were displayed on the Android screen as two 2D images exposing to both eyes of the VR headset wearer since a 3D version of emotional films were not readily available (see fig. 5.11 for an illustration of using two 2D images fitting the two eyes using the Android smartphone).

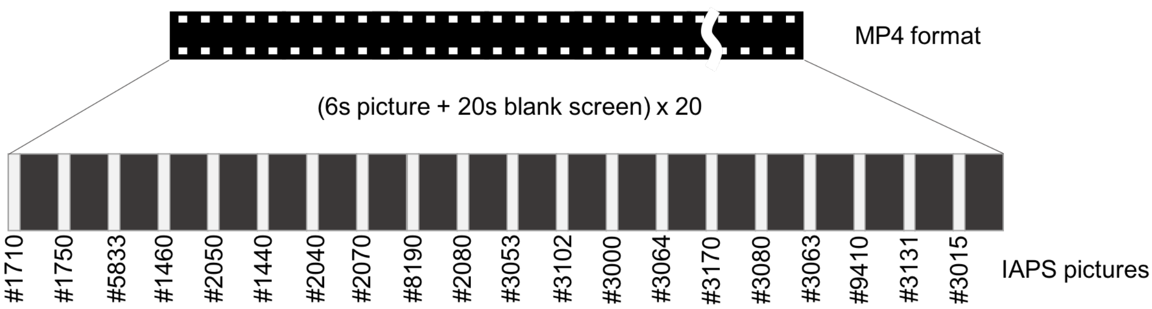

FIGURE 5.8: Convert IAPS still pictures into an MP4 film clip

[4]https://developer.android.com/guide/topics/media/media-formats
[5]https://handbrake.fr

5.5 Wireless Data Collection

A synchronised data collection of physiological responses during emotion elicitation was done through a wireless connectivity based on the BLE protocol. Bio-signal measurement using the sensing glove (see section 5.3) was sampled at 100Hz and converted into digital signals, the *SPW2* module then packaged the four different digital bio-signal into a BLE package and ready to transmit. Once the Android smartphone connected and subscribed to the *SPW2* using a Generic Attribute Profile (GATT) server/client connection, the raw sensor data was collected continuously using a BLE notification channel. For every package received from the *SPW2*, the Android smartphone would append it to the end of a file stored in its internal filing system. Each file was timestamp and identifiable by both the type of stimulus used for inducing emotions (i.e. the filename of the stimulus) as well as the unique identity of the sensing glove for physiological measurements (i.e. the MAC address of the *SPW2* module). The unique identity for the *SPW2* is reserved for future expansion to include multiple sensing gloves in the same experiment using the *emotionWear* framework. The whole process from applying the stimuli for emotion elicitation, to activating the data transmission of physiological signals, to storing the data as a file and uploading to a cloud storage, was managed through synchronisation and timing control by a program running on the Android smartphone. Figure 5.9 depicts the scheduling of various tasks and actions related to the controlling of the whole emotion perception and response process using a sequence diagram. Due to the limited space in the sequence diagram, the details for each task or action are further explained in the corresponding table 5.4.

Recording of the physiological responses through the four bio-signals was done before the actual application of the emotional stimuli in order to allow the capture of the baseline response during a rest period of one minute. The one minute baseline period was chosen according to the previous literature research which reveals a variation from 10 seconds to a couple minutes (see Chapter 2 section 2.3), thus, we chose to use an average value of one minute due to the lacking of a standard yet. The timing for the application of emotional stimuli was controlled by the central controller implemented on the Android smartphone, and the detection of the OR response was also achieved according to the hypothesis made by previous studies. The validation of a true emotion elicitation and the corresponding recognition algorithm is further explained in section 5.6 where the raw physiological response

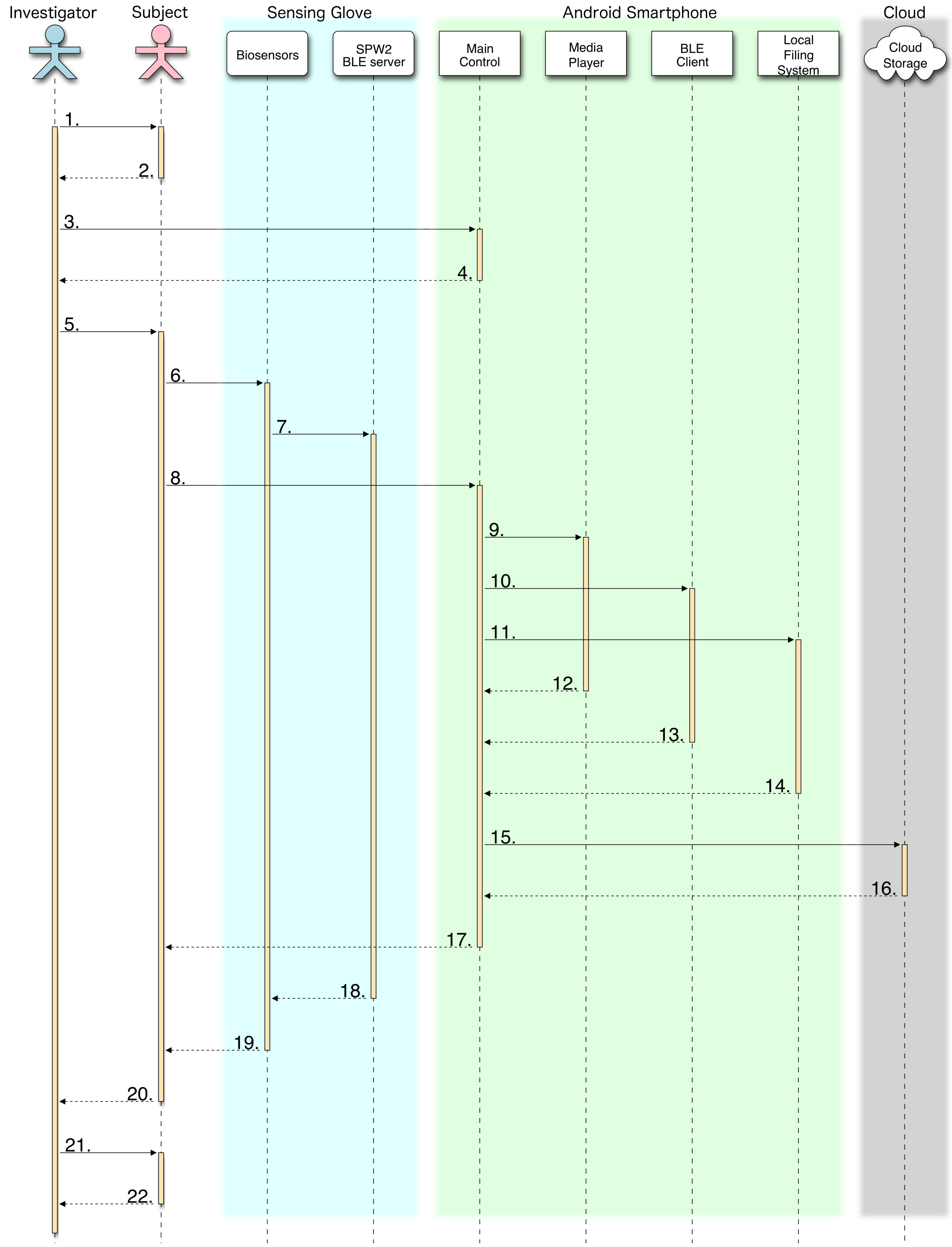

FIGURE 5.9: Sequence Diagram for the *emotionWear* framework (details for each task or action in the sequence diagram are listed in table 5.4)

TABLE 5.4: Detail Description of the Sequence Diagram in Figure 5.9

Sequence	Descriptions
1, 2	Investigator did a pre-study survey with the human subject before conducting the experiment, a form was filled in with some general details of the subject anonymously (e.g. age, gender, etc.). The form also listed the preference for each human subject in selecting stimuli, for example, the subject who was afraid of horror movies would not be exposed to film clips in the fear category. Details of the forms and the protocol for conducting the experiment can be found in section 5.7.
3, 4	After getting the consensus from the subject, the investigator customised the stimuli (i.e. the emotional still pictures and the chosen film clips) in chronologically order to be exposed to the subject through the VR headset. The investigator, through the user interface of the smartphone, arranged the selected media files such that they could be played back in sequence.
5	Investigator helped install the VR headset and the sensing glove to the human subject making sure the hardware and software were all functioning correctly.
6, 7	The sensors of the sensing glove started measuring the bio-signals of the human subject once the glove was attached and the raw data was sent to the *SPW2* module immediately. The *SPW2* collected the digital bio-signal data after the ADC which converted the analogue signals to their digital form. However, nothing was transmitted from the BLE channel yet until a BLE client was connected to the server on the *SPW2*. All the collected data was lost without a BLE connection since the *SPW2* would not store the raw data in its own memory.
8	The human subject, when ready, activate the smartphone to start the experiment by pressing the button on the VR headset. The experiment was then formally started.
9	Three actions started once the activation was confirmed by the subject. The first action was the starting of the media player which played the first media file configured by the investigator according to the requirement of the subject. A one minute blank screen was inserted allowing the collection of a baseline physiological response which adjusted the actual reading afterwards. The next media file would be played once the last one finished, and a one minute baseline period would be added automatically.
10	The second action was the connection to the *SPW2* to collect the physiological responses. The main control class messaged the BLE client to connect to the server on the *SPW2* based on a GATT subscription service, and the raw digital bio-signals were transmitted from the *SPW2* to the smartphone as a package with 20 bytes notification payload. This BLE notification collected the playload even in the baseline period gathering the reference response before the actual emotion elicitation session.
11	The third action was the appending of the payload package to a file in the local storage of the smartphone. This "Local Filing System" class created a file at the beginning with its filename consisted of the name of the media file and the timestamp empowering the synchronisation at the data analysis process (see section 5.6 for details). Once the play back of the current media file was complete, the file was closed and a new file with different name would be created accordingly.
12	When all media files were successfully played and the controller class started terminate the experiment after receiving messages from other classes.
13	The BLE client disconnected from the server on the *SPW2*.
14	The file for storing the payload packages was also closed.
15, 16	Controller class put all files containing the payload to a folder which would be synchronised with the cloud automatically. A folder had been created and a configuration was setup enabling the synchronisation between the remote (i.e. cloud storage) and local folder.
17	A user interface prompting the human subject through the screen alerting the completion of the experiment.
18, 19, 20	Investigator helped remove the VR headset and sensing glove from the human subjects after competing the experiment.
21, 22	The investigator conducted a post-study survey with the human subject and collected the comments for the study and also asked the subject to sign the acknowledge form which allowed the subject to contact for any follow up actions.

data is analysed through iPython.

A stable wireless data collection relied on three major areas in developing the *emotion-Wear* framework, they were the sampling frequency for collecting the raw bio-signal data from the sensing glove into its digital representation, the wireless protocol for establishing a reliable low power data transmission, and the technologies for registering and storing the raw data for further processing in emotion recognition.

First, the data acquisition for physiological measurement relied on the Python program running on the *SPW2* module. Referring to the sequence diagram (fig. 5.9), the biosensors installed in the sensing glove measured the four bio-signals continuously once the power was supplied and the data was sent to the *SPW2* module through the I2C ports (see the block diagram in fig. 5.2). The *SPW2* packaged the raw digital bio-signals into a 20-byte payload ready for transmitting to the BLE client when a GATT connection was made with the Android smartphone. The payload format is illustrated in fig. 5.10 where only 17 out of the 20 bytes were used for delivering the physiological responses.

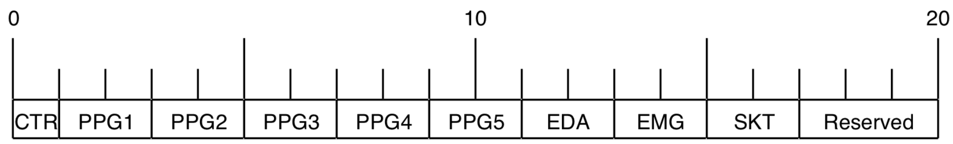

FIGURE 5.10: Structure of the BLE payload packet (20 bytes)

A one byte loop counter CTR assigned a sequence number from 0 to 127 (or 0x00 to 0x7F with the first bit stayed zero) to each BLE packet and it was used in the iPython data analysis stage for verifying any missing packets when the CTR bytes for two consecutive packets were not aligned (i.e. not in sequence). Two bytes (from 0x0000 to 0xFFFF) were used to represent each bio-signal sampling at 100Hz. A total of ten bytes were used for the PPG data to increase the sampling rate from 100Hz to 500Hz for a better accuracy on heart rate measurement since five PPG samples were sent in one packet. The decision on increasing the PPG sampling frequency was based on a literature review on cardiovascular measurement which shows that high frequency components are required for HRV analysis. EDA, EMG and SKT each occupied two bytes of the payload based on a 100Hz sampling. Three bytes were reserved for future expansion such as the adding of more physiological measurements, but these three bytes were discarded for the current study. From a literature review of past psychophysiological research, there are many studies comparing the sampling frequencies of different physiological signals particularly for emotion and they range from as low as 5Hz to a few kilohertz (Camm et al., 1996; Jeyhani et al., 2015; Mahdiani et al., 2015; Shaffer and Ginsberg, 2017). However, there is no standard on the optimum sampling frequency for each type of bio-signals for emotion study. A 100Hz was used as the basis for the current study since it was used in previous research and the current platform using BLE connectivity could support this frequency without performance degrade. Problem was found on older version Android smartphones running on a lower speed CPU and less memory since the Android OS (Operating System) could not affort to schedule the callback function handling with the normal phone operations. Finally, a Google Pixel smartphone running Android 7 was used for the *emotionWear* platform as the central controller.

Secondly, the selection of low power data transmission protocol from contemporary WSN technologies that are commercially available. The criteria for choosing a wireless connectivity for data communication follows the DUI concept which empowers an intuitive H2M interaction through unnoticeable tangible interfaces (Hui and Sherratt, 2017). Although it was still far from a completely disappeared user interface but methods had been put to mimic a DUI environment, for examples, miniaturised sensors were adopted in the sensing glove and armband trying not to interfere with normal operations (see section 5.3), and the collection of sensing data was forced to go wireless enabling a data transmission free from attaching to desktop instrument through wires. Only standard wireless protocols were considered since proprietary protocols would require a lot of development efforts to achieve a stable and reliable connectivity which was not the main interest in the current study. Moreover, there were many low power wireless protocols available for WSN with ample resources on hardware modules and software libraries ready to be acquired on the present platform. Table 5.5 lists the contemporary wireless protocols suitable for WSN with their applicability to the *emotionWear* framework. Finally, according to the comparison of different WSN protocols, we chose to use BLE because of its cost effective implementation, and the availability of technologies by the time of study.

Finally, an Android smartphone acting as the central controller integrated the selection and application of emotion stimuli through the VR headset (section 5.4), the collection of

TABLE 5.5: WSN Wireless Protocol Selection

WSN protocols	**Applicability to *emotionWear***
Cellular WSN connectivity (Sahoo, Hota and Barik, 2014) 2G/3G/4G networks	Cellular networks using the existing 2G/3G/4G infrastructures provide a convenient connection for attaching indoor or outdoor sensors to the Internet based on popular technologies such as SMS or GPRS data. A GSM modem module with SIM card installed can be online purchased where an MCU talks to the module and communicates wirelessly to the Internet through a set of AT commands. However, many obstacles prevent its usage to prevail in building cost effective WSN, for examples, the requirement of a data service boosts the operating cost to a high side, the very high power consumption during data transmission to the base stations, and the unstable performance on signal strength in indoor applications. Therefore, cellular network connectivity for biosensors is not suitable for the present study.
Low Power Wide Area Network (Barker and Hammoudeh, 2017) Sigfox LoRa/LoRaWAN NBIoT LTE-M	An alternative wide area sensor network is found from the Sigfox technology which provides outdoor connectivity for sensors through fixed base stations, but its proprietary protocol; restricted data uplink and downlink per day; and limited area of coverage disqualify its usage on continuous bio-signal measurement. LoRaWAN, although not a cellular network, covers a wide area due to its sub-GHz open standard protocol. However, a gateway is needed to convert LoRa to TCP/IP protocol makes it complicated to use for the current study. NBIoT and LTE-M are relatively new members of the 4G LTE network, thus, although they are full of promises for WSN connectivity in the IoT, they are still not ready to fly. Wide area WSN seems not a good candidate to be included in the present experiment due to the high cost, or the complicated infrastructure, or the limited quantity in data transmission, or the immature technology by the time of study.
Indoor WSN protocols (Barker and Hammoudeh, 2017; H. Wang and Fapojuwo, 2017) Zigbee Z-Wave Thread BLE WiFi	Mesh networking technologies such as Zigbee, Z-Wave and Thread are common protocols for indoor WSN and their low power nature and long range coverage based on mesh configurations seem to be good WSN candidates, the only reason that they were not selected in the current study was the overall cost of implementation which involved the acquiring of the particular modules for each sensor and a gateway for protocol conversion. Leaving behind were WLAN or WiFi and BLE technologies. Both of them can transmit data continuously once a channel is established, and off-the-shelf modules can be easily acquired at low cost. Moreover, these two technologies are normally found as built-in connectivity in most smartphone nowadays. Final choice was placed on BLE since it was relatively low power during transmission, and the smartphone could act as a BLE to WLAN gateway when real time data analysis was required.

the physiological responses through the sensing glove (section 5.3), the packaging and uploading of raw physiological signals from local storage to the cloud, and the scheduling of all related activities based on a Java program. This program written specifically for the Android operating system also allowed an investigator to setup and customise the experiment for the human subjects with different needs (see section 5.7 for details). The two objects under the "Sensing Glove" (shown in light blue background in fig. 5.9) were connected together to serve the purpose of collecting the bio-signals from the wearer, and transmitted wirelessly all the measured bio-signals in their digital form through BLE (see section 5.3). The tasks under the "Android Smartphone" block (shown in light green background in fig. 5.9) were implemented as Java classes during the programming stage. Figure 5.11 illustrates a complete assembly of the wireless data collection for the *emotionWear* framework and consists of the sensing glove, the VR headset and the Android smartphone with a Java program implementing the UI for controlling the whole operation.

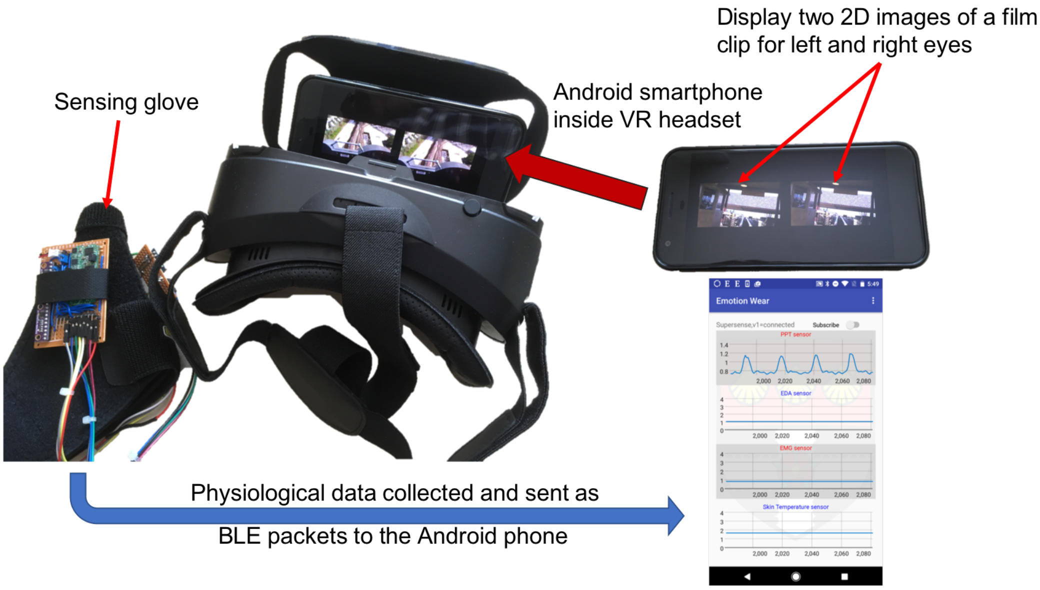

FIGURE 5.11: Complete Assembly of Wireless Data Collection for *emotionWear*

5.6 Data Analysis

Data analysis based on the response-stimulus synchronisation concept is the basis for designing the *emotionWear* framework. Figure 5.12 illustrates the implementation of the concept according to the sequence diagram depicted in fig. 5.10 where the a blank screen of 10 seconds is used to collect a baseline for each individual physiological measurement once the participant activates a test (marked in fig. 5.12 as "Test starts"), the playback of the selected film clip follows the baseline period inducing emotion to the participant through the VR headset. Physiological response collection embedded in the wireless BLE data packets kept transferring to the Android smartphone at 100Hz during the testing with EDA, EMG, SKT sampling at 100Hz and PPG sampling at 500Hz. Analysis of the OR activities at the perceived emotional scenes enabled the hypothesis (Chapter 1 section 1.2) to be proven when the signal trends of selected features matched with the ANS specificity. Perceived emotions are (1) the emotional scenes for each film clip which have been tagged from the surveys in previous research (Gross and Levenson, 1995; Schaefer et al., 2010), and

(2) the moments of switching between emotional pictures in the IAPS film clip compiled for the present study (section 5.4). These perceived emotional moments were used to verify the OR activities during the analysis, however, the perceived emotions might not be the same as the induced emotions (Tian et al., 2017) so inconsistent results were expected.

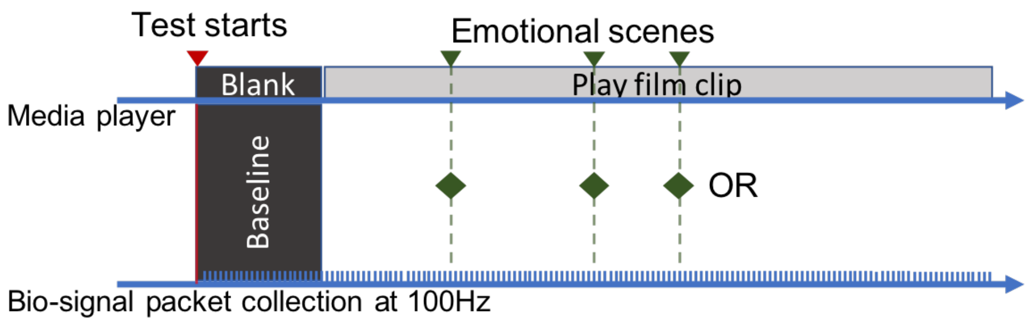

FIGURE 5.12: response-stimulus Synchronisation

Python and R are two competitive languages for data analysis and they both can fulfil the requirements of the current research analysing the physiological response data for emotion recognition. No detailed comparison had been done and no particular preference was put on either language, iPython notebook (now called Jupyter Notebook[6]) was finally chosen since it provided a convenient Python platform based on a web browser interface and the familiar Python syntax made the learning curve more gentle. Libraries from the Python community were acquired for data processing of the raw stimulation and response data files (e.g. numpy[7], pandas[8], scipy[9], moviepy[10], etc.).

The target achievement for the data analysis process was a proof of the hypothesis for the current research listed in section 1.2. The concepts from IoT and DUI presented in Chapter 3 and Chapter 4 respectively helped design the *emotionWear* framework to intuitively induce emotions and collect the concomitant physiological responses through wearable sensors and wireless data collection mentioned above. The raw physiological responses have been analysed to reveal the emotion recognition based on the proposed response-stimulus synchronisation hypothesis, and the steps to get to the final conclusion are as follows:

[6] https://jupyter.org
[7] https://www.numpy.org
[8] https://pandas.pydata.org
[9] https://www.scipy.org
[10] https://zulko.github.io/moviepy/

Step 1) Stimulus and Response Preprocessing

Data processing on raw stimuli was done in advance to provide a consistent format for analysis since the film clips under study were having different durations and frame rates. Indexing to each frame was achieved in this preprocessing stage for later synchronising with the physiological responses from various participants. Missing data due to RF interference during wireless data collection was a problem that also needed to be tackled before the actual data analysis was began by filling the data through statistical approach.

Step 2) Psychophysiological Feature Extraction

Feature extraction from the preprocessed raw physiological response data was then performed using the Python libraries which took out the required components from the four bio-signals. For examples, a heart rate feature could be extracted from the interbeat intervals in the PPG signal, a clean tonic level and the standard deviation of EDA/EMG/SKT could be extracted after applying a digital filter minimising the associated noise picked up during biomedical measurements.

Step 3) Orienting Response Detection

OR is hypothesised in the current research as a synchronisation clock for triggering a decoding of the associated psychophysiological response promoted by an emotional perception. The detection of the OR activities was performed using the Python data processing capability where the phasic EDA and HR deceleration were measured as a trigger for an emotion recognition process. The OR activities were also treated as indicators for validating true emotion elicitations.

Step 4) Autonomic Nervous System Specificity Comparison

Once an OR activity is detected, the trends of the physiological features were then compared with the hypothesised ANS specificity stated in section 5.3. Predefined window was applied to the signal trend calculations which compared with the assumed thresholds for emotion recognition based on ANS specificity.

Step 5) Null Hypothesis Testing

In order to compare the results obtained from the hypothesised response-stimulus synchronisation with the unsynchronised data, a statistical significance test was finally done using the null analysis Python library based on the concept of Null Hypothesis.

5.6.1 Stimulus and Response Preprocessing

In order to analyse different stimuli and bio-signals in a single platform, pre-processing of the audiovisual stimulation files and the raw response database were done before the actual analysis was begun. First, an index was assigned to each frame of the film clips for synchronising with the physiological responses. A straight forward way for synchronisation with the 100Hz physiological response is to expand by duplication of the 30 frames MP4 format to 100 frames per second, but it will just add the burden on the Python processing power without any benefit for the analysis since many frames are having very similar contents. Although there is no standard frame rate for encoding video files, a range from 24fps to 60fps is recommended for normal movie watching without flickering to the naked eyes. Moreover, there are recommendations from surveillance camera companies suggesting that 10fps is good enough for catching details of most normal human activities[11]. Therefore, a set of still images based on 10fps for each MP4 file was extracted to be synchronised with every 10 data packets of physiological responses (see Figure 5.13).

Using the iPython notebook, a folder was created for each film clip storing all the frame images converted from the video file at 0.1 second interval (e.g. a 5.3 minutes film clip generated 5.3 x 60 x 10 = 3180 images at 10fps). Refers to the Python code "*iPython codebox: frame creation from film clip*", the frame generation function creates a directory call movieName_frames where all the frame images in .jpg were stored. All film clips including the IAPS picture film clip have gone through this pre-processing to generate the 10fps JPEG images for further analysis. Whenever the signal trends of the bio-signals matched with the predefined ANS specificity, the corresponding frame that induced the emotion was retrieved and this frame was presumably the emotional scene inducing the particular emotion state.

[11] https://ipvm.com/reports/frame-rate-surveillance-guide

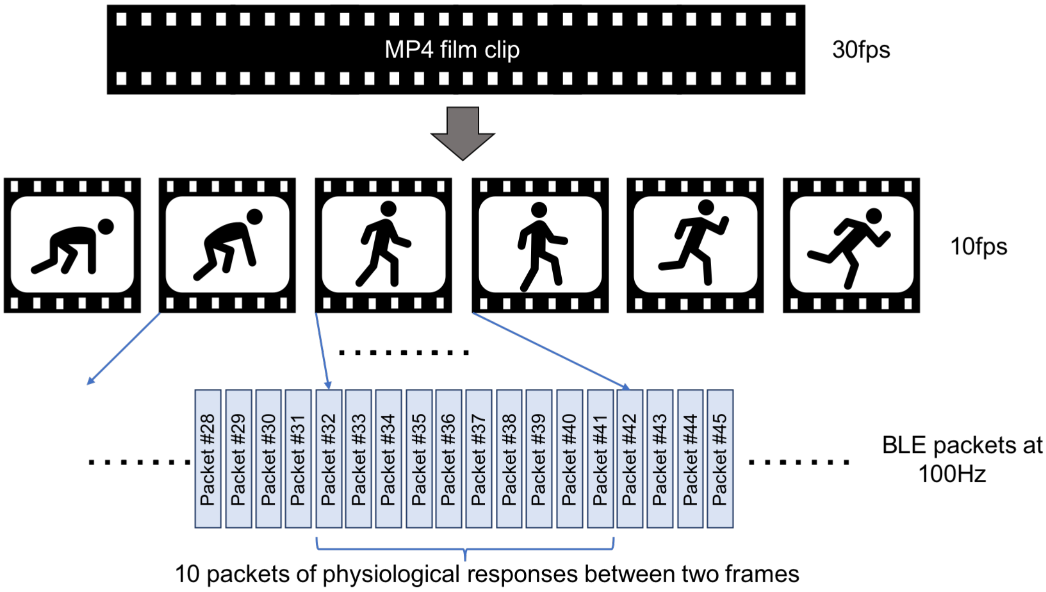

FIGURE 5.13: MP4 film clips and the associated BLE packets

iPython codebox: frame creation from film clip

```
from moviepy.editor import VideoFileClip
movieFile = "Movie01.mp4" # eplace with the name of each film clip
movieName = movieFile.partition(".")[0] #remove the file extension
clipFull = VideoFileClip(movieFile)
length = clipFull.duration * 10 #create index for frame at 10fps
for i in range(0, int(length)):
    clip_time = i/10
    #generate frame images at 10fps using clipFull.save_frame function
    clipFull.save_frame(movieName + "_frames/frame_" + str(i) + ".jpg", t=clip_time)
```

Pre-processing on the physiological responses was also needed to be done on every raw data file collected. Each raw physiological response data in the current study was targeted for one participant emotionally induced by one film clip for easy referencing. The purposes for this data pre-processing were listed below:

a) Data extraction for individual bio-signals

   Other than the loop counter byte and the three reserved bytes at the end of each packet, the PPG signal occupied 10 bytes, EDA occupied two bytes, EMG occupied two bytes and SKT occupied the final two bytes. The “pandas” and “numpy” libraries were used to separate the biosignals into data arrays for analysis using common libraries.

b) Filling missing BLE packets

   Packet lost happens in wireless data transmission due mainly to the RF interference such as link congestion, it becomes even worst in the 2.4GHz frequency spectrum where WLAN (802.11 b/g/n), BLE and microwave oven are all coexisted at the same time. The loop counter byte was used specifically as an index for checking how many packets were missing in the current analysis and filled up with the average values.

c) Reindexing the database

   Unique index was assigned to identify each item of the data arrays for the whole database after filling the missing packets.

d) Baseline and normalisation

   The first 10 seconds for each physiological response database were used to collect the baseline levels for adjusting the actual bio-signal variations during the emotion elicitation stage (i.e. physiological response after the first 10s). Normalisation of the baseline adjusted data arrays was also done to get a comparison signal trends instead of the degree of variations, since the main purpose of the current study was focused on the response-stimulus synchronisation hypothesis.

Refers to the Python code "*iPython codebox: filling missing packets*" for the code that extracts the individual bio-signals and fills up the missing data arrays using manual interpolation. The built-in interpolation functions from pandas have not been used in the raw signal preprocessing due to the flexibility of filling up the loop counter which cycles every 128 counts.

5.6.2 Psychophysiological Feature Extraction

Getting the correct details for data analysis on individual psychophysiological response followed the preprocessing of the raw bio-signals mentioned above where the required features were extracted through the Python libraries, for examples, the heart rate variations from PPG, and the signal trends of EDA, EMG & SKT. Examination of the signal features was done with the OR hypothesis acting as the synchronisation clock between stimuli and psychophysiological responses.

The extraction of heart rate variations from PPG data started from a calculation based on the Interbeat Interval (IBI) measurement using the following formula 5.1:

$$HR = \frac{60 \times Sampling\ Frequency}{Interbeat\ Interval} \tag{5.1}$$

iPython codebox: filling missing packets

```
import pandas as pd
import numpy as np
rawFile = 'biosignal.txt' #replace with the name of each physiological data file
#extract bio-signals and remove last three bytes
dt = np.dtype([('CTR','>u1'),('PPG1','>u2'),('PPG2','>u2'),('PPG3','>u2'),
    ('PPG4','>u2'),('PPG5','>u2'),('EDA','>u2'),('EMG','>u2'),('SKT','>u2'),
    ('NU1','>u1'),('NU2','>u2')])
raw = np.fromFile(rawFile, dtype=dt)
data = pd.DataFrame(raw)
data = (data.loc[:, 'CTR':'SKT']).assign(SEQ = 0, MIS = 0)
#find missing data packets
max = 128; missed = 0; currentmissed = 0
for i in range(len(data)-1):
    currentmissed = data.CTR[i+1]+(max*(data.CTR[i+1]<data.CTR[i]))-data.CTR[i]-1
        data.at[i+1, 'MIS'] = currentmisse)
    missed = missed + currentmissed
    currentmissed = 0
    data.at[i+1, 'SEQ'] = i+missed+1
#renew index with missing rows
new_index = pd.Index(np.arange(0, data.SEQ[len(data)-1]), name='SEQ')
data = pd.DataFrame(data.set_index('SEQ').reindex(new_index))
#manual linear interpolation to fill up missing rows
for i in range(len(data)):
    count = data.MIS[i]
    if( np.isnan(count) and count!=0):
        for c in range(int(count)):
            data.at[i-c-1, 'CTR'] = data.CTR[i-c]-1+(max*(data.CTR[i-c]==0))
            data.at[i-c-1, 'PPG1'] = int(data.PPG1[i]-((data.PPG1[i]-
                data.PPG1[i-count-1])*(c+1))/(count+1))
            data.at[i-c-1, 'PPG2'] = int(data.PPG2[i]-((data.PPG2[i]-
                data.PPG2[i-count-1])*(c+1))/(count+1))
            data.at[i-c-1, 'PPG3'] = int(data.PPG3[i]-((data.PPG3[i]-
                data.PPG3[i-count-1])*(c+1))/(count+1))
            data.at[i-c-1, 'PPG4'] = int(data.PPG4[i]-((data.PPG4[i]-
                data.PPG4[i-count-1])*(c+1))/(count+1))
            data.at[i-c-1, 'PPG5'] = int(data.PPG5[i]-((data.PPG5[i]-
                data.PPG5[i-count-1])*(c+1))/(count+1))
            data.at[i-c-1, 'EDA'] = int(data.EDA[i]-((data.EDA[i]-
                data.EDA[i-count-1])*(c+1))/(count+1))
            data.at[i-c-1, 'EMG'] = int(data.EMG[i]-((data.EMG[i]-
                data.EMG[i-count-1])*(c+1))/(count+1))
            data.at[i-c-1, 'SKT'] = int(data.SKT[i]-((data.SKT[i]-
                data.SKT[i-count-1])*(c+1))/(count+1))
            data.at[i-c-1, 'MIS'] = 0)
#save the file after all missing packets are filled
data.to.csv(rawFile.partition('.')[0]+'FM.txt')
```

The Python code implementation of the above calculation is illustrated in "*iPython codebox: calculate heart rate from PPG*". IBI was extracted from a clean PPG signal using a peak detection algorithm: the find_peaks function from the scipy libraries[12]. Interpolation based on pandas was used to extend the array of detected peaks to fill up the whole range, and a rolling average algorithm was adopted to act as a low pass filter smoothing the signal. The rolling window winHR of ten second was chosen to eliminate unwanted fluctuation within the period, and the assumption was based on the audiovisual stimuli presented as movie which normally would not change too quickly to catch viewer's attention. Finally, a

[12]https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.find_peaks.html

normalisation was performed to keep a constant signal level for later comparison.

iPython codebox: calculate heart rate from PPG

```
#Calculate heart rates from PPG signals
#  finds peaks and extracts interbeat interval
#  calculates discrete heart rate and fills up with interpolation
import numpy as np
import pandas as pd
from scipy.signal import find_peaks
peaks, _ = find_peaks(data.PPG1, height = 14400, distance = 60)
peaks = peaks[1:]
HR = pd.DataFrame(np.ediff1d(peaks), index=peaks[:-1])
start = HR[0].iloc[0]
end = HR[0].iloc[-1]
HR = HR.reindex(np.arange(0,len(data.PPG1),1))
HR[:peaks[0]] = start
HR[0].iloc[-1] = end
HR = HR.interpolate(method='cubic') #extend array into full range
HR = HR.rolling(winHR, min_periods = 1).mean() #low pass filter using rolling average
HR = (HR - HR.min()) / (HR.max() - HR.min()) #normalisation for easy comparison
```

Sampling frequency for PPG at 100Hz was finally chosen for the data analysis in the *emotionWear* instead of the previously proposed 500Hz. A comparison was conducted to review the differences between the two sampling frequencies on the PPG signal. Focus was directed on the peak detection accuracy which was the basis for the heart rate calculation. A Python code executing the comparison on detecting peaks using both 100Hz and 500Hz PPG data collected from one response file is illustrated in "*iPython codebox: peaks detection comparison*". The result showed that the same number of peaks were detected for both signals composed of 100Hz and 500Hz raw data, and the correlation between these two arrays of peaks revealed a very strong association at 0.9999999991194309 (i.e. the correlation is very close to +1). Therefore, the data analysis for the current research was based on 100Hz sampling for all bio-signals including the PPG.

Although it is not in the interest of the present research, literature review has proposed other feature analysis utilising the IBI from the PPG signal in both time and frequency domains. Details of the Python formulas can be found from Chapter 6 where popular HRV features (such as SDNN, SDSD, RMSSD, LF, HF, etc.) were extracted using the *emotionWear* framework. Signal processing for other bio-signals were done through the rolling average function with different rolling windows: ten seconds for EMG (winEMG) and SKT (winSKT), and 1 second for EDA (winEDA) since the analysis showed that the variations on EDA was faster based on the synchronisation with the stimuli. "*iPython codebox: feature extraction on EDA, EMG and SKT*" presents the Python code for data processing on these three

iPython codebox: peaks detection comparison

```
#Compare peak detection accuracy between 100Hz and 500Hz
import numpy as np
import pandas as pd
from scipy.signal import find_peaks
dataFile = 'iapsFM.txt' #preprocessed response file for IAPS film clip
data = pd.read_csv(dataFile)
#detect peaks for 100Hz sampling frequency
peaks1, _ = find_peaks(data.PPG1, height=14400, distance=60)
#detect peaks for 500Hz sampling frequency
PPG = data.loc[:, 'PPG1':'PPG5'] #select 500Hz PPG samples
PPG = PPG.stack() #turns row data into single column
peaks5, _ = find_peaks(PPG, height=14400, distance=60*5)
#compare number of peaks detected with different sampling frequencies
print(len(peaks1), 'peaks at 100Hz, ', len(peaks5), 'peaks at 500Hz')
print('Correlation between two peaks:  ',np.corrcoef(peaks1, peaks5)[0,1])
### the result is:
### 608 peaks at 100Hz, 608 peaks at 500Hz
### Correlation between two peaks:0.9999999991194309
```

bio-signals. Figure 5.14 shows a graph illustrating the psychophysiological responses stimulated by the IAPS film clip (section 5.6.1) based on the processed bio-signals mentioned above (i.e. HR, EDA, EMG, and SKT). This graph is a typical response-stimulus synchronisation analysis where the concomitant responses represented by the four physiological features were extracted from the raw data when emotional scenes were exposed to a participant.

iPython codebox: feature extraction on EDA, EMG and SKT

```
# Extracting features from EDA/EMG/SKT signals
#  low pass filter using rolling average, then
#  normalise signals for consistent comparison
EDAraw = (data.EDA.max() - data.EDA)/ (data.EDA.max() - data.EDA.min())
EDA = EDAraw.rolling(winEDA, min_periods = 1).mean()
EDAstd = EDAraw.rolling(winEDA, min_periods = 1).std()
EMGraw = (data.EMG - data.EMG.min()) / (data.EMG.max() - data.EMG.min())
EMG = EMGraw.rolling(winEMG, min_periods = 1).mean()
EMGstd = EMGraw.rolling(winEMG, min_periods = 1).std()
SKTraw = (data.SKT - data.SKT.min()) / (data.SKT.max() - data.SKT.min())
SKT = SKTraw.rolling(winSKT, min_periods = 1).mean()
SKTstd = SKTraw.rolling(winSKT, min_periods = 1).std()
```

It is relatively easier to identify the emotional scenes for the IAPS film clip since a switching from a blank screen to an emotional picture is supposed to be an emotional moment. The emotional scenes from other film clips using in the current study (see table 6.2 for details) are not as straightforward as the IAPS film clip but survey was done identifying those particular moments that most people agreed as the emotional scenes. The numbers on the x-axis refer back to the IAPS picture references where each tick mark on the x-axis shows the time when the reference picture is exposed to a participant through the VR headset, and

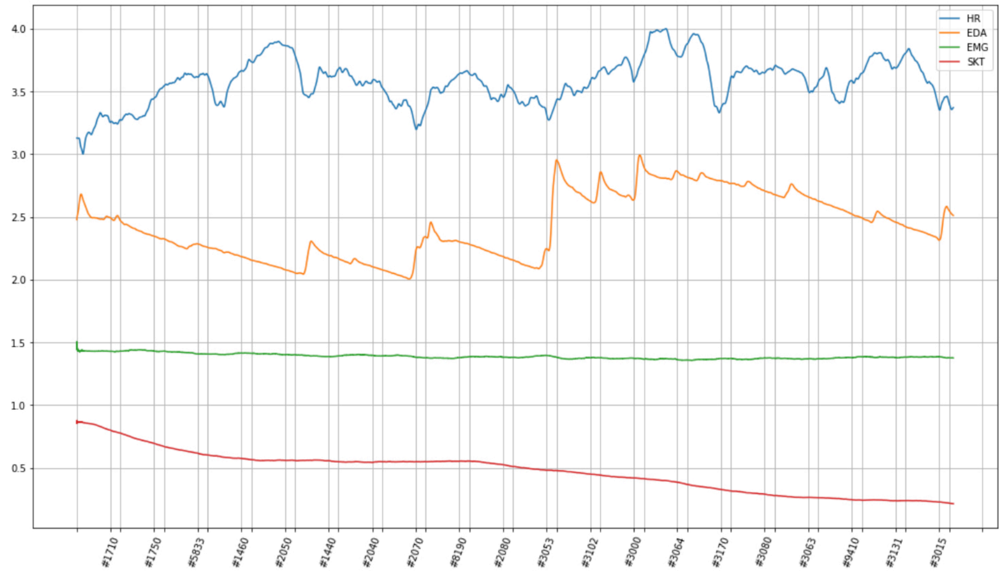

FIGURE 5.14: Response-Stimulus Synchronisation (extracted from Appendix D response graph “iaps 01” for participant EP1)

the synchronised bio-signal responses are displayed on the horizontal axis.

In fig. 5.14, the most significant change on the response happens at the time switching from a group of high valence pictures to the first low valence picture #3053, and this image is an emotional scene of unpleasantness (the ‘BurnVictim’ picture, see table 5.2). Noticeable variations occur on EDA and SKT, where EDA has been hypothesised as the activation of OR. Thus, the current study also relies on the EDA signal trend as the OR attention indicator or the synchronisation clock for an emotional response (see Chapter 2 section 2.4). SKT referring to the fingertip temperature is part of the ANS specificity showing a subtle decrease in temperature due to the variation of the skin blood flow (see Chapter 2 section 2.3), it can be treated as a sign of depression for emotion recognition when OR is detected (i.e. an emotional elicitation is induced). EMG signal hasn’t shown a significant variation that allows a reliable detection and has been ultimately discarded from all records, further investigation should be done to review its effectiveness in emotional recognition. The HR is a complicated feature which is affected by many physiological functions (see Chapter 2 section 2.3) and a significant deceleration is also part of the OR hypothesis, so it is also being used in the present study for emotion recognition together with the pattern matching of ANS specificity.

5.6.3 Orienting Response Detection

OR is hypothesised as an indication of human attention for a changing environment where emotional perception is induced by a novel stimulus (see Chapter 2 section 2.4). Capturing the OR activities based on an abrupt change of the phasic component of an EDA signal was one of the possibility for OR detection, and it was used together with the HR deceleration as the response-stimulus synchronisation clock in the current study. The signal trends of the mean values of the physiological features previously extracted were then compared with the ANS specificity hypothesis to recognise the five basic emotions.

Detecting OR was the first step in the data analysis for emotion recognition where a sharp increase on the skin conductance of an EDA signal was assumed as the hypothesised synchronisation clock. Validation was then performed using a HR deceleration which was also hypothesised as a physiological indication of an OR activity. The phasic component of an event-related skin conductance (or ER-SC) is assumed to be triggered by an OR which innervates the eccrine glands especially on the palms and the soles of the feet activating a higher level of sweat secretion so as to boost the skin conductance level after a stimulation event. A typical ER-SC EDA signal is depicted in fig. 5.15 which contains three parts as described by Boucsein (2012). Part ① is the latency period which activates the ER-SC from stimulation and is normally within one to two seconds, part ② is the time from an on-set to a peak amplitude of the ER-SC, and part ③ is the recovery period where 50% amplitude drop is defined as half of the recovery time and a complete recovery ends at 63% of the full ER-SC amplitude. The whole ER-SC pulse (i.e. ② + ③) is normally within three seconds.

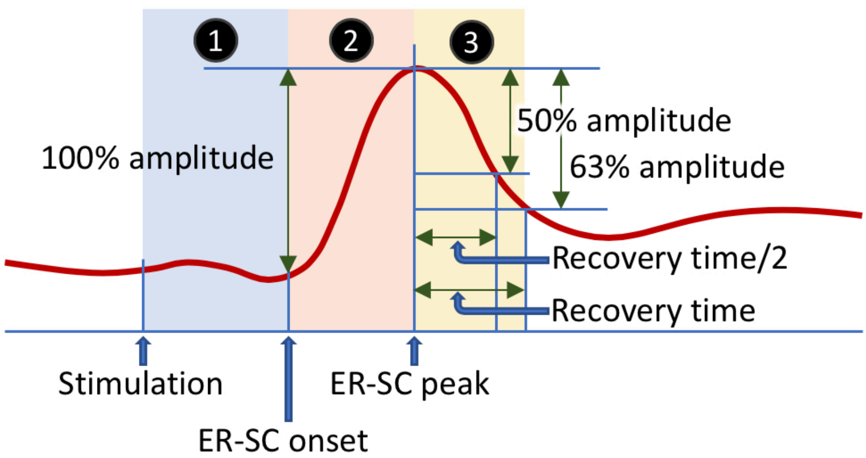

FIGURE 5.15: Event Related Skin Conductance of an EDA signal (triggered by an OR activity)

Once an ER-SC was identified, an HR deceleration was checked to validate a true OR occurrence. A two-second window was used centering at the peak of an ER-SC to verify the HR signal trend, where a negative trend validated an OR capture. The Python code illustrated in "*iPython codebox: OR capturing*" implements the algorithm according to the above descriptions. A peak detection library from scipy was used to extract the phasic EDA signal and detected part ② of an ER-SC, then a HR deceleration threshold check was followed to complete the validation. Detecting the OR based only on this ER-SC feature using the Python libraries is straight forward but creating a generic algorithm to capture the ER-SC signals requires more conditional statements to reject other similar events in real time EDA signal such as non-stimulation-specific SC responses, motion artefacts, and other startle reflex. In order to limit the scope of research, the finding of a generic algorithm was not included in the current study.

iPython codebox: Orienting Response Capturing

```
# Calculate OR activities
#  find peaks and extracts the ER-SC phasic EDA signals
#  compare HR before and after the ER-SC and verify the OR moment
import numpy as np
from scipy.signal import find_peaks
OR = [] # array to store validated OR activities, i.e.ER-SC + HR deceleration
peaks, _ = find_peaks(EDA, height = 0.3, width = 300, prominence = 0.06)
for x in peaks:
    selected = HR[x-100:x+100]# select 2s HR period
    coefficients, residuals, _, _, _ = np.polyfit(range(len(selected)),selected,1,
        full=True)
    if coefficients[0] < 0:# detect HR deceleration
        OR.append(x)
# the OR array now contains all validated OR moments
```

5.6.4 Autonomic Nervous System Specificity Comparison

ANS specificity comparison performed the pattern matching for emotion recognition when a validated OR was detected according to the last section. The signal trends for the three features extracted from the processed physiological signals (i.e. HR, EDA and SKT) were compared with the thresholds and classified the responses according to a truth table (table 5.6) which was derived from the empirical proven and generally agreed ANS specificity illustrated by Kreibig's summary (see section 5.3).

TABLE 5.6: ANS Specificity Comparison Truth Table for *emotionWear*

Emotion States	HR	EDA	SKT
Joy/Happiness	1	1	1
Fear/Anger	1	1	0
Sadness	0	0	X
Disgust	0	1	X

X = don't care

Inconsistent variations on SKT were reported from previous psychophysiological research in sadness and disgust, thus, the current study treated this feature as "don't care" for pattern matching. However, the signal trends for EDA enabled the differentiation between sadness and disgust emotion states once HR was decelerating. Fear and anger were known to be hard to distinguish and the present study would not try to separate them although methods had been suggested (Ax, 1953; Stemmler, Aue and Wacker, 2007). They were treated as the same during the specificity testing, and this decision didn't affect the final result since there was no anger emotion reported during the study. An extension of the algorithm could be implemented to set apart these two emotion states, but this was not included in the present experiment.

Signal trends using linear regression for HR and SKT were calculated through a window of 60 seconds starting from a validated OR pulse. However, a special handling was required for the EDA bio-signal. According to previous literature review, only the tonic component was compared before and after the OR occurrence and thus, the phasic part of the EDA described as ER-SC in the last section was needed to be removed (Lim et al., 1997; Boucsein, 2012; Braithwaite et al., 2013). Figure 5.16 illustrates the selection of the EDA signal where the tonic levels before and after the ER-SC are compared to get the trend of variation. A window of 60 seconds has also applied to get the average for comparison, and the Python code implementing this ANS specificity comparison is shown in "*iPython codebox: ANS Specificity Comparison*".

5.6.5 Null Hypothesis

Despite the controversy of statistical significance testing, the current study still used the tool of Null Hypothesis to act as a comparison between the analysis obtained with and without the OR as a verification of the response-stimulus synchronisation hypothesis (Levine et al.,

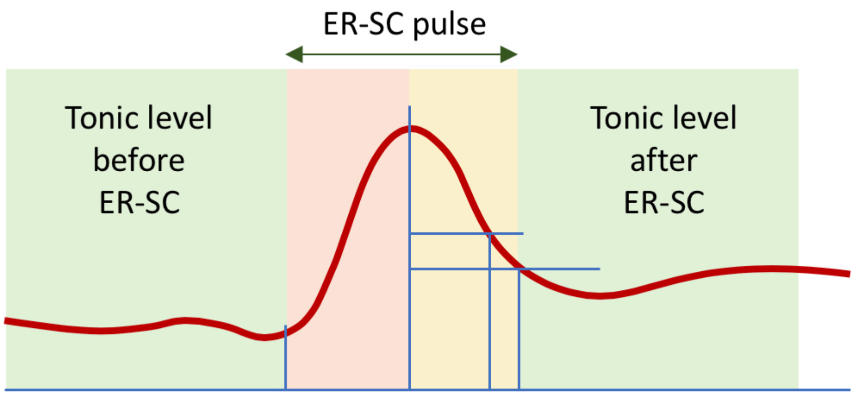

FIGURE 5.16: EDA Tonic Level Extraction

2008; Greenland et al., 2016). The rejection of the Null Hypothesis may illustrate that significant differences exist between emotion recognition results with and without a validation of emotion elicitations. The null and alternative hypotheses are defined as below:

Null Hypothesis
Response-Stimulus Synchronisation algorithm does not affect an emotion recognition using physiological responses.

Alternative Hypothesis
Response-Stimulus Synchronisation algorithm is necessary in emotion recognition where the timing for decoding the concomitant physiological response is dependent on the moment of a true emotion elicitation.

The data analysis for null hypothesis was based on the Pearson correlation coefficient measuring the linear relationship between the datasets from the two hypotheses mentioned above, and a p-value was generated as a prove of rejection (Bruton, Conway and Holgate, 2000; Sedgwick, 2012). The Python library for Pearson (scipy.stats.pearsonr[13]) was chosen to perform this analysis due to its easy of use and ample references from the Python community. The signal trends calculated from the windows after the OR occurrence contributed to the first dataset for the alternative hypothesis, and the rolling average using a 60-second window for the physiological responses collected from the whole film clip became the null hypothesis's dataset for comparison. These two datasets were passed to the *pearsonr* function to calculate the r coefficient and the p-value for the current analysis (see Chapter 6 for the result of comparison). The Python code for getting the p-value from the Pearson

[13]https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.pearsonr.html

iPython codebox: ANS Specificity Comparison

```
# ANS specificity pattern matching
#  Calculate signal trends for HR, EDA and SKT after OR is identified
#  and predict the emotion state according to a truth table
import numpy as np
from scipy.signal import find_peaks
ANS = []# array to store ANS specificity results
# ANS truth table
ANS_input = np.array([[0,0,0],[0,0,1],[0,1,0],[0,1,1],[1,0,0],[1,0,1],[1,1,0],
    [1,1,1]])
ANS_output = np.array(['Sadness','Sadness','Disgust','Disgust','NA','NA','Fear/Anger',
    'Joy'])
# main loop for ANS specificity pattern matching, OR is an array contains all
    validated OR moments
for o in OR:
    # ANS specificity check on HR, calculate the signal trends
    OR_HR = HR[o:o+6000]
    coefficients, residuals, _, _, _ = np.polyfit(range(len(OR_HR)),OR_HR,1,full=True)
    if coefficients[0] > HR_threshold:
        HRans = 1
    else:
        HRans = 0
    # ANS specificity check on EDA, compare average values before and after OR
    EDA_before = EDA[o-6300:0-300].mean()
    EDA_after = EDA[o+300:o+6300].mean()
    if EDA_after > EDA_before:
        EDAans = 1
    else:
        EDAans = 0
    # ANS specificity check on SKT, calculate the signal trends
    OR_SKT = SKT[o:o+6000]
    coefficients, residuals, _, _, _ = np.polyfit(range(len(OR_SKT)),OR_SKT,1,
        full=True)
    if coefficients[0] > SKT_threshold:
        SKTans = 1
    else:
        SKTans = 0
    ansIndex = np.where((ANS_input == [HRans, EDAans, SKTans]).all(axis=1))
    ANS.append(ANS_output[ansIndex[0]])
# the ANS array now contains all ANS specificity results showing the predicted
    emotion states for each OR moment detected
```

coefficients (second variable) is shown in "*iPython codebox: Null Hypothesis Analysis - p-value calculation*".

Despite the fact that the p-value is commonly treated as the major criteria for statistical significance, researchers have recently criticised the reliability and reproducibility of previous study results based on p-value only (Halsey et al., 2015). In order to achieve a strong position for rejecting the null hypothesis, the statistical power may also depend on the effect size and sample size (Anderson, Kelley and Maxwell, 2017). The "pearsonr" python library can calculate the effect size and the "statsmodel" [14] can help estimate the minimum sample size through a power analysis algorithm (Sullivan and Feinn, 2012). The *iPython codebox: minimum sample size calculation* illustrates the Python code to estimate the minimum sample

[14] http://www.statsmodels.org/dev/index.html

iPython codebox: Null Hypothesis Analysis - p-value calculation

```
# Calculate the p-values to reject the Null Hypothesis
#  uses datasets from successful and unsuccessful predictions of HR, EDA and SKT
#  and calculates the p-value using pearsonr with the correct emotion datasets
from scipy.stats import pearsonr
# Calculation of HR p-values with and without OR validation
HRafterOR# HR trends dataset after validated OR
HRwithoutOR# HR trends dataset without OR
HRcorrect# HR dataset for correct emotion states
HRp_afterOR = (pearsonr(HRafterOR, HRcorrect))[1]
HRp_withoutOR = (pearsonr(HRwithoutOR, HRcorrect))[1]
# Calculation of EDA p-values with and without OR validation
EDAafterOR# EDA trends dataset after validated OR
EDAwithoutOR# EDA trends dataset without OR
EDAcorrect# EDA dataset for correct emotion states
EDAp_afterOR = (pearsonr(EDAafterOR, EDAcorrect))[1]
EDAp_withoutOR = (pearsonr(EDAwithoutOR, EDAcorrect))[1]
# Calculation of SKT p-values with and without OR validation
SKTafterOR# SKT trends dataset after validated OR
SKTwithoutOR# SKT trends dataset without OR
SKTcorrect# SKT dataset for correct emotion states
SKTp_afterOR = (pearsonr(SKTafterOR, SKTcorrect))[1]
SKTp_withoutOR = (pearsonr(SKTwithoutOR, SKTcorrect))[1]
```

size to achieve the stated statistical power.

5.7 Experiment Design

An emotion recognition experiment was designed based on the *emotionWear* framework described above where an integration of emotion elicitation, physiological response capturing, wireless data collection and cloud uploading was successfully complete. All activities for an experiment were arranged according to the sequence diagram illustrated in fig. 5.9. An investigator helped each human subject prepare for a test under a controlled environment using the VR headset. The raw physiological responses were uploaded to the Google cloud storage and were analysed offline by the iPython data analysis utilities based on the proposed concept of response-stimulus synchronisation and the hypothesis of OR. The study results were finally compiled into an academic paper published in a peer review journal (see Chapter 6 for details).

The research protocol for the current study requires a collection and study of the data derived from human participants and is therefore subject to an ethical clearance process, *iPython codebox: minimum sample size calculation*

```
# Calculate the minimum samples size to achieve the stated statistical power
#  using power analysis algorithm
from scipy.stats import pearsonr
from statsmodels.stats.power import TTestIndPower
# Calculation of HR effect size with OR validation
HRafterOR# HR trends dataset after validated OR
HRcorrect# HR dataset for correct emotion states
HRe_afterOR = (pearsonr(HRafterOR, HRcorrect))[0]
# Calculation of EDA effect size with OR validation
EDAafterOR# EDA trends dataset after validated OR
EDAcorrect# EDA dataset for correct emotion states
EDAe_afterOR = (pearsonr(EDAafterOR, EDAcorrect))[0]
# Calculation of SKT effect size with OR validation
SKTafterOR# SKT trends dataset after validated OR
SKTcorrect# SKT dataset for correct emotion states
SKTe_afterOR = (pearsonr(SKTafterOR, SKTcorrect))[0]
# Perform power analysis to calculate the minimum sample sizes for HR, EDA and SKT
#  using alpha as 0.05, effect size from calculations above, and power
#  is the p-value
analysis = TTestIndPower()
HRsize = analysis.solve_power(HRe_afterOR, power=HRp_afterOR, nobs1=None,
     ratio=1.0, alpha=0.05)
EDAsize = analysis.solve_power(EDAe_afterOR, power=EDAp_afterOR, nobs1=None,
    ratio=1.0, alpha=0.05)
SKTsize = analysis.solve_power(SKTe_afterOR, power=SKTp_afterOR, nobs1=None,
    ratio=1.0, alpha=0.05)
```

table 5.7 lists the different stages of the research protocol for the present experiment. According to the Guidance Notes from the University of Reading[15], any research protocol involving human participants requires an approval from the Research Ethics Committee. The current study was no exception and an application with all the details of how the experiment was conducted and all materials being used for human interactions were submitted to the committee. Approval was finally granted after two revisions (a total of three submissions) which gradually improved in exploring the details of how human participants were exposed to the emotion elicitation processes and how follow up actions were handled (see Appendix B for the approved research protocol, and Appendix C for the responses to comments attached with the final submission).

Similar to most psychological research, a statistical analysis methodology was adopted to analyse the human responses due to the individual differences (Lykken, 1968), thus, ten human subjects were recruited to participate in the experiment. The statistical result would be more accurate with a larger database but the limited time frame and budget in the current study had restricted the expansion of the number of participants. The participants were made up of half male and half female with an average age of 44.6 years and a standard deviation of 10.67. Personal health conditions were also specified during the recruitment in

[15] http://www.reading.ac.uk/internal/academic-and-governance-services/research-ethics/

TABLE 5.7: Research Protocol for Emotion Recognition using *emotionWear*

Stages	**Remarks**
1. Ethical Clearance	Due to the involvement of human participants in the current study, an ethical clearance process was required to protect the data collection from the subjects and their well beings (see Appendix B for the details of the approved research protocol).
2. Recruitment of subjects	After the research protocol was approved by the Ethics Committee of the University of Reading, the recruitment of participants was conducted by email and invitation following the restrictions stated in the protocol. Ten participants, half female and half male, were recruited for taking part in the emotion recognition experiment.
3. Pre-study Survey	Referring to fig. 5.9, the investigator conducted a pre-study survey to each individual explaining the details of the experiment, such as the purpose of the study, the risks for participating the test, the rights of the participant, the privacy protection of personal data, etc. The investigator helped each participant to fill in a Questionnaire (see Appendix B for the format) which collected general details of the participants without exposing their identity. This Questionnaire also allowed each participant to select the appropriate types of stimuli for the emotion elicitation process according to their preferences. The participants knew in this stage that they could stop the experiment any time they felt uncomfortable.
4. During the experiment	The experiment was conducted according to the sequence of tasks listed in the sequence diagram (fig. 5.9). Participants worn the VR headset and the sensing glove with the help from the investigator. The emotion induction started when the participant activated the process and the concomitant physiological responses were collected accordingly.
5. Post-study Survey	The tests were completed and the investigator helped remove the headset and sensors from the participants and continued to fill in the partially completed Questionnaire with the feelings of the participants also registered for comparison. A Consent form was signed and a photocopy was taken by each participant after completing the tests. The format of the consent form can be found in appendix B.
6. Offline Data Analysis	Raw physiological response data for each test was uploaded to the cloud and was offline analysed after completing the experiment using iPython. An Apple MacBook Pro laptop computer was used to download the raw data for data processing such as filling missing BLE packets, calculated the signal trends and predicted the emotion through ANS specificity. All records were password protected for security and anything related to the identity of the participants for each database was removed for privacy purpose.

order that there was no particular diagnosed medical symptom affecting the physiological measurements, for examples, cardiovascular irregularity that affected the normal heart rate variations, or sweat glands related diseases such as hyperhidrosis and hypohidrosis that affected the normal sweating activities specifically on the palms, or unusual blood supply such as Raynaud's disease that affected the normal fluctuations on fingertip temperature, or muscle disorders that affected the daily muscle contraction. Other qualities for protecting personal privacy, preventing potential risk for emotion elicitation, and tackling post-study abnormality were all taken care of before, during and after the experiment where the research protocol was predefined and approved before the application.

5.8 Conclusions and Future Works

A novel emotion recognition framework *emotionWear* based on the response-stimulus synchronisation concept, the hypotheses of basic emotion and ANS specificity was design from scratch. The synchronisation between the application of stimulations, the collection of the concomitant physiological responses were under the control of a Java program running on an Android smartphone. Despite the fact that the *emotionWear* framework was implemented with common off-the-shelf technologies, an example using audiovisual stimuli through a VR headset for inducing emotions and collecting emotional responses through wearable biosensors wirelessly demonstrated the application of DUI in the IoT environment. Applying the synchronisation clock to the data analysis processes illustrated the improvement in emotion recognition using simple pattern matching with the ANS specificity and further proved that a validation of a true emotion elicitation was critical for an effective emotion recognition, for example, using the concept of cognitive attention through the OR activities. The result from an experiment using the *emotionWear* was translated into a paper published in an academic journal, and it further proved the proposed hypothesis that response-stimulus synchronisation was a missing technology for establishing an artificial sixth sense system (Hui and Sherratt, 2018).

Response-stimulus synchronisation may be a missing technology verified by the *emotionWear* for implementing an artificial sixth sense system to the general public, however, the lacking of standards in the field of emotion recognition using computing engineering could be another major obstacle preventing it from prevailing in everyday use. During the design and implementation phases of the *emotionWear*, agreeable standards from the definition of emotions, the debate between discrete and dimensional views of emotions, the argument for basic and constructed emotions, the timing for collecting the physiological responses for emotion recognition, and the specification on ANS specificity were all absent. Research from a neuropsychological perspective seems to speed up a convergence of concepts and theories through a peeking into the human brains, thus, a consensus of the theories related to emotions may soon be reached. However, all parameters being used in the *emotionWear* framework can easily be adjusted to improve the performance once discoveries are found from new research to provide empirical evidences in practical applications.

The current study using the *emotionWear* plays a major role in the future smart homes based on the prevailing IoT concept. The seven major requirements for building smart homes in smart cities (Hui, Sherratt and Díaz-Sánchez, 2017) propose the necessary ingredients for a modern intelligent home when IoT technologies work together. A novel Intelligence user interface enabling multiple human users interacting with multiple computers will be a major challenge for IoT to be successful in internetworking humans and machines globally, and the interfacing through contents may become a core part of this IoT interactions. Knowing what the humans (i.e. users) want through an artificial sixth sense system which understands and predicts human emotions under different environments may be a major step for IoT to provide bespoke computer output through stimulation.

The DUI concept (see Chapter 4) enables the interface with computer using contents instead of the traditional menu driven approach (Hui and Sherratt, 2017), and it has also built the groundwork for the *emotionWear* framework especially on the computer output for emotion stimulation through a VR headset and the computer input for physiological response capture through wireless biosensing. Although the existing computer interfaces for the *emotionWear* is far from invisible but the concept of DUI focuses on unnoticeable instead of being disappeared. The VR headset isolates the wearer from the surrounding world minimising the interference from the outside during emotion induction, and the wireless connectivity empowers the data communication with wearable biosensors for psychophysiological response collection.

An experiment was conducted with the *emotionWear* framework using human subjects. Their emotions were induced through the VR headset, their physiological responses were captured through the sensing glove, and their emotional responses were analysed using the Python code listed in the previous sections. The design of the experiment protocol was targeted to protect the human subjects in terms of their mental and physical health as well as their privacy, and at the same time a proper procedure was laid down to minimise the number of variables and get the required results. The ethics committee approved the protocol after a couple revisions before starting the recruitment of participants. Results of the experiment was compiled and published as an academic paper under a peer review process, where the details could be found from the next chapter (Chapter 6).

Flexibility was built into the original design of the *emotionWear* framework such that additional stimuli of various types (e.g. haptic, gustatory, or olfactory stimulus), and the extra sensing facilities could be included in the framework as long as the connectivity methodology is compatible with the Android smartphone. Wired biosensors with digital outputs can be connected to the *SPW2* module through an I2C or SPI bus, alternatively the connection to the spare ports of the ADC chip is also available for analogue bio-signals. Wireless sensor connections are also possible using BLE or WLAN when the sampling rate is properly adjusted not to interfere with the normal program flow. Enhancement on data analysis to increase the recognition accuracy can be done by fine tuning the thresholds in the different signal processing stages such as:

a) HR extraction

   HR depends on the threshold level for detecting the peaks and the minimum width between the interbeats. The current setting is only fit for the existing datasets, a generic version may require further research on setting individual thresholds for various groups according to age, gender, or health conditions.

b) Anger and Fear

   The ANS specificity between anger and fear emotion states are now treated as the same but subtle differences have been found from previous study. More experiments and data analysis must be conducted to review the differences in order to distinguish them during an emotion recognition process through the existing pattern matching algorithm.

c) OR Detection

   Peak detection on the standard deviation of EDA is not a comprehensive method for decoding the OR activity through an ER-SC pulse (see section 5.6.3). Rejecting similar signal variations other than the ER-SC is required for a generic approach for triggering the true OR events.

d) Null Hypothesis

   The sample size using in the Pearson correlation coefficient calculation was too small for a result with high confident level, more experiments with higher number of participants may be able to improve the results. The samples taken from the experiment in the current study were not enough to illustrate the confidence level for rejecting the null hypothesis and it was a mistake overlooked during the planning stage. The sample size calculation can be found from Chapter 6 section 6.4.

e) Scope of emotion recognition

Only the basic five emotion states are being used for the current research and this is the hypothesis generally agreed by most researchers studying emotion. Extending the scope to include more emotion states will be a logical next step but it is not a simple task unless the arguments related to emotions are settled. A cross disciplinary research such as neuropsychology may be a break through in the future.

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Chapter 6

Coverage of Emotion Recognition for Common Wearable Biosensors

This chapter presents the results of an experiment using the *emotionWear* framework. The details of the design of *emotionWear* and the protocol of the experiment are described in Chapter 5, which shows the selection criterion and processes of all related components involved in building the framework, the theories and hypotheses behind the selections, the integration technologies connecting all components to work together seamlessly, the data analysis algorithm and methodologies for emotion recognition, and the research protocol involving human participants in the experiment. The current chapter focuses on the application of the *emotionWear* in exploiting the coverage of emotion recognition using common off-the-shelf biosensors based on a response-stimulus synchronisation hypothesis. The results reveal the pre-processing of emotion recognition process which shows the importance of validating an emotion elicitation through the OR occurrence before applying an ANS specificity matching algorithm for emotion recognition.

A version of this chapter has been published open access in the Journal of Biosensors.

Hui, T.K.L. and Sherratt, R.S. 'Coverage of Emotion Recognition for Common Wearable Biosensors'. Biosensors 8(2), 30 (2018), DOI: 10.3390/bios8020030.

The present research proposes a novel emotion recognition framework for the computer prediction of human emotions using common wearable biosensors. Emotional perception promotes specific patterns of biological responses in the human body, and this can be sensed and used to predict emotions using only biomedical measurements. Based on theoretical and empirical psychophysiological research, the foundation of autonomic specificity facilitates the establishment of a strong background for recognising human emotions using machine learning on physiological patterning. However, a systematic way of choosing the physiological data covering the elicited emotional responses for recognising the target emotions is not obvious. The current study demonstrates through experimental measurements the coverage of emotion recognition using common off-the-shelf wearable biosensors based on the synchronisation between audiovisual stimuli and the corresponding physiological responses. The work forms the basis of validating the hypothesis for emotional state recognition in the literature and presents coverage of the use of common wearable biosensors coupled with a novel preprocessing algorithm to demonstrate the practical prediction of the emotional states of wearers.

6.1 Introduction

Emotion has not been conclusively defined after more than a century of research (W. James, 1884; Deigh, 2014), but the significance of the functions of emotion are less arguable than its definition (Keltner and Gross, 1999; Levenson, 1999; Frijda, 2016). The promotion of emotional responses not only can balance our physical health through the nervous and endocrine systems to reach the goal of homoeostasis (Cacioppo, Tassinary and G. Berntson, 2007), recent research on neuroimaging also proves that our everyday behaviour is a close integration of both cognition and emotion (Wells and Matthews, 2014; Pessoa, 2015). Moreover, human beings located in different contexts (or environments) (Maren, Phan and Liberzon, 2013), having different experiences (Bergado, Lucas and Richter-Levin, 2011), having physiological impairments due to health (Critchley and Harrison, 2013) or ageing (Shiota and Neufeld, 2014) or having mental illness (Henry et al., 2016) may experience abnormal emotional behaviours when the same stimuli are applied. Consequently, emotion recognition may become a personalised service according to individual's spatial and temporal situations (Barrett, 2014; Quigley and Barrett, 2014; Marwitz and Stemmler, 1998; Stemmler and Wacker, 2010; Duclot et al., 2016). A major problem in common emotion recognition system lies in a successful elicitation of target emotions for further processing since the perceived emotions may not be the induced emotions (Schubert, 2013; Tian et al., 2017).

The measurement of human emotions is a crucial step in AI to enable computers to have affective communication with humans (Picard, 1997; Picard, 2010). Ubiquitous computing using the Internet of Things (IoT) has implemented AI technologies into smart homes and smart cities (Hui, Sherratt and Díaz-Sánchez, 2017), since it is forced to interact with human users by sensing, recognising and predicting their intentions based on the prevailing phenomenon of DUIs (Hui and Sherratt, 2017). Emotional responses are best captured by a DUI through natural and intuitive interactions since human perception of emotions may consist of both conscious and unconscious processes (Winkielman and Berridge, 2004; Smith and Lane, 2016). Remote and on-body sensing are both good DUI candidates for individual emotion recognition, but remote sensing such as visual data capturing or radio frequency leveraging is still application limited, especially in ambulatory activities; thus, wearable sensors may be a better choice in pervasive sensing applications. However, wearable "things" in IoT normally face challenges such as limited processing power, size constraints and limited battery capacities. Therefore, a meticulous selection of embedded sensors with a lightweight methodology for emotion recognition is a basic requirement in designing affective wearables in the IoT environment and forms the focus of this chapter.

Section 6.2 presents the related work done by previous research. The experiments, tools and the framework design based on DUI for the current research are depicted in Section 6.3. This is followed by the result of the experiments in Section 6.4. Further discussion in Section 6.5 analyses the validation of emotion elicitation and the coverage of emotion recognition for each individual and combined wearable sensors. In the last section, we conclude our findings and lay down the groundwork for future research.

6.2 Related Work

Emotions can be recognised by mapping specific patterns of the measured biosignals based on physiological responses promoted by an emotional perception (Ax, 1953; Levenson, 1992). Many researchers have produced empirical evidence showing that the human brain orchestrates the ANS and endocrine systems, which then innervate the visceral organs to produce autonomic specificity (Kreibig, 2010; Cutmore and D. A. James, 2007; Norman, G. G. Berntson and Cacioppo, 2014). A comprehensive study of an affective wearable illustrated by Picad (Picard and Healey, 1997) set off the application in wearable physiological measurements on emotion recognition, which is a sub-branch of affective computing (Picard, 1997). During the past two decades, research on emotion wearables has emerged aiming to enable ambulatory emotion recognition by incorporating the advancement in sensing technologies (Cima, 2014; Yoon, Sim and Cho, 2016), networking technologies (Wac and Tsiourti, 2014; Chen et al., 2017) and emotion recognition methodologies (Mauss and Robinson, 2009; Landowska, 2014). Research on emotion recognition for wearables has focused mainly on using common biomedical sensors, and the collection of biosignals as a training dataset is fed to a classifier based on modern machine learning algorithms. Recognition accuracy varies according to the choice of sensor signals and their derivatives, the placement of sensors, the presentation and types of stimuli, as well as the different classification algorithms (Kragel and LaBar, 2014; Verma and Tiwary, 2014; Khezri, Firoozabadi and Sharafat, 2015). Recent research indicates an upward trend in the number of features extracted from those physiological signals promoted by emotion perception for boosting the prediction accuracy based on supervised learning algorithms, and that number can even exceed 100 in certain research methodologies (Kim and André, 2008; Godin et al., 2015; He, Yao and Ye, 2017). Principle Component Analysis (PCA) may help reduce the number of effective variables, but the stable control of a high number of features is still a significant challenge particularly in wearable devices (Howley et al., 2006; Shlens, 2014). However, original research on autonomic specificity (Wechsler and Jones, 1928; Ax, 1953; Averill, 1969; Stemmler, 1989; Levenson, Ekman and Friesen, 1990; Levenson, 1992; Kreibig, 2010) did illustrate a simple relationship between some basic discrete emotional states and the associated physiological responses such as the variations in heart rate, the magnitude of changes in skin conductance, the subtle fluctuations in fingertip temperature and also the relatively complicated contractions on facial and skeletal muscles. Figure 6.1 depicts a simplified relationship between the nervous systems, some of the affected visceral organs, common wearable biosensors for emotional state recognition and the ANS specificity that were demonstrated for some discrete emotions from previous empirical studies (Kreibig, 2010). The figure only shows those autonomic patterns about which most researchers agree, and the emotion recognition process of the current study also relies on this pattern. Motor programs activating the skeletal muscles of the face and certain parts of the body are also believed to be concomitant to the ANS during emotional responses and are normally treated as one of the contributors to the physiological specificity for emotions (Kret et al., 2013; Gothard, 2014; Shafir, Tsachor and Welch, 2016).

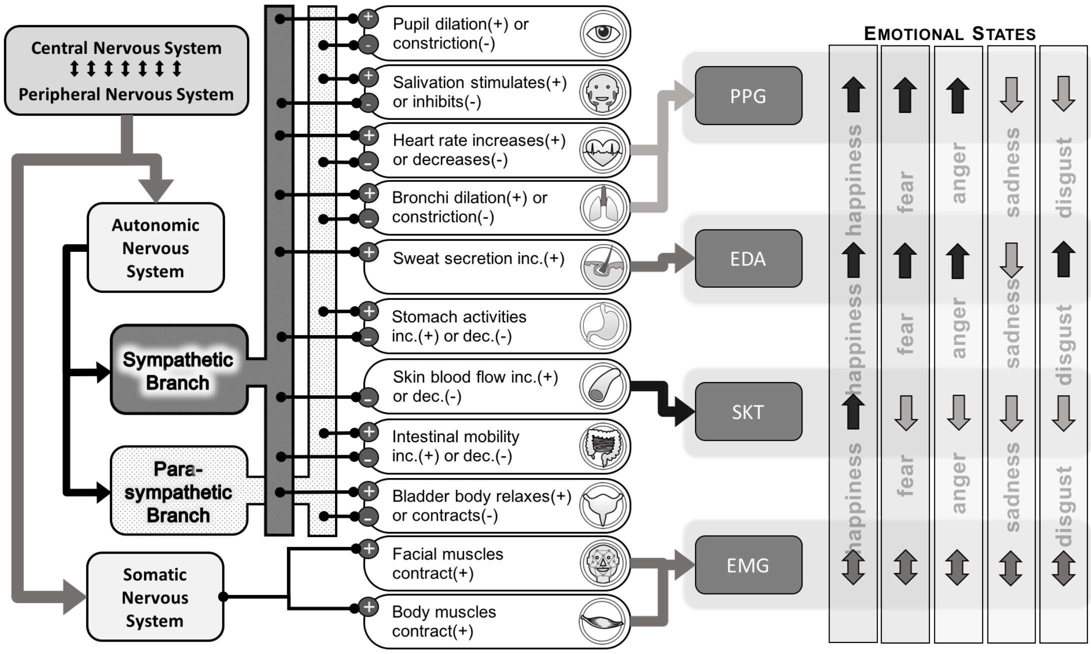

FIGURE 6.1: Simplified emotion recognition using common wearable bio-sensors

Collecting the correct moment of physiological data for feeding a well-trained statistical prediction machine learning algorithm is equally important in affective application, especially in the personalised smart services provided by IoT environments where an identification of affective moment should initiate certain operations. OR has been heavily researched as an indication of attention to environmental change for animals and humans (Graham and Clifton, 1966; Bradley, 2009), and the OR hypothesis is further strengthened by the P3 component of the event-related potential in neuroscience research based on previous electroencephalography (EEG) measurements (Barry, Steiner and De Blasio, 2016; MacDonald and Barry, 2017). Cardiac deceleration and skin conductance changes are common indications for initiating the OR process when novel audiovisual stimuli are applied to humans activating emotional perceptions. Recent OR research also hypothesises that the variations of cardiac deceleration can distinguish between pleasant and unpleasant emotions through audiovisual cues (Codispoti, Surcinelli and Baldaro, 2008; Rooney, Benson and Hennessy, 2012; Bradley, Keil and Lang, 2012). A synchronisation between audiovisual stimuli and the concomitant physiological variables may be able to capture this OR process, which facilitates the validation of a successful emotion elicitation for further analysis and operations.

According to Kreibig's review (Kreibig, 2010), there is no standard for the averaging interval of the physiological measurement (varying from 0.5 second to 300 seconds and most often being 30 seconds and 60 seconds), which is the temporal quality of the elicited emotions. Therefore, the correct moment of the measurement interval from start to finish defines whether the details of the emotional responses are captured.

There has been much research about emotion recognition based on physiological patterning, such as those using machine learning, as previously discussed and that will not be explored in this chapter. The current research focuses on the preprocessing of emotion recognition, particularly on the analysis of the validation of successful affective moments stimulated by audiovisual cues, and the coverage of common wearable biosensors.

6.3 Materials and Methods

The experimental protocol for this study was approved by the Research Ethics Committee of the University of Reading #SBS17-18 10. Five male and five female adults with an average age of 44.9 years (STD = 10.7) without any diagnosed medical conditions (e.g., diabetes, heart disease, sweating disorders such as hyperhidrosis or hypohidrosis) were chosen to participate in the study. Each participant was presented with several types of emotional stimuli, and their corresponding physiological responses were recorded using the four types of non-invasive wearable biosensors mentioned in this chapter. Two out of the ten subjects, a male and a female, were invited to extend the testing for a longer version of audiovisual stimuli by watching a TV program eliciting "joy" emotions in order to demonstrate real-time continuous emotion recognition using the current framework.

6.3.1 *emotionWear* Framework

A framework was built for the current research as a complete emotion recognition system from stimulation of emotions to registration of the corresponding physiological responses. Synchronisation between stimuli and responses is established for easy monitoring and referencing by using an Android smartphone acting as a central control centre. Figure 6.2 depicts a block diagram of the whole *emotionWear* framework which consists of the following components (the references (i) (ii) (iii) ⓐ ⓑ ⓒ etc. in the descriptions below refer to the labels in the drawing):

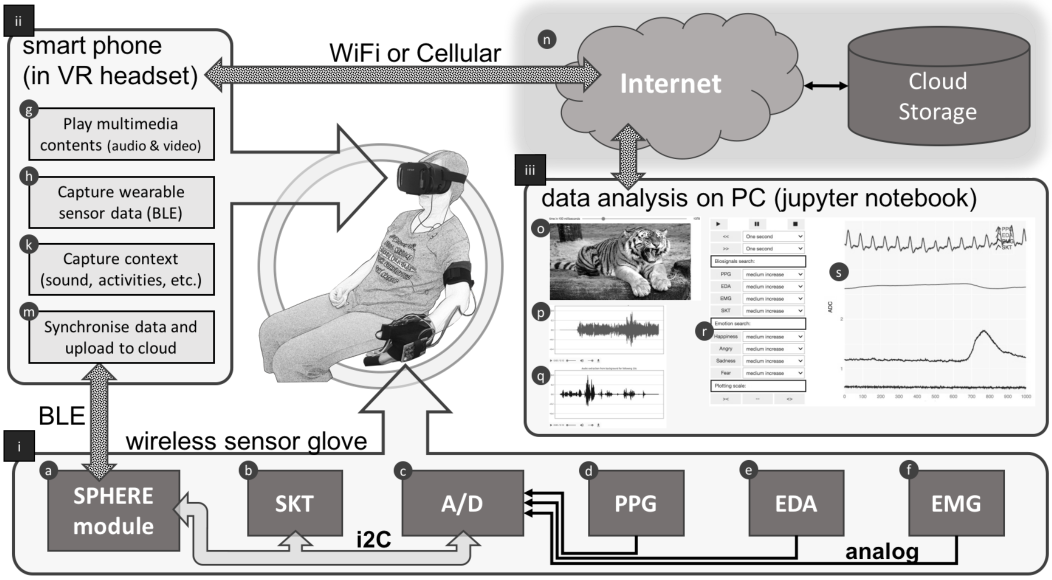

FIGURE 6.2: Block diagram of textitemotionWear Emotion Recognition Framework

(i) Wearable Sensing Glove

Biomedical sensors (PPG, EDA, SKT and EMG) are mounted on a sensing glove made from a wrist support with velcro straps for easy installation and setup. The PPG and EDA sensors are attached to the inside of the glove touching the thenar region of the hand of a subject, the SKT digital temperature sensor is attached to the tip of a middle finger, and the EMG sensor is attached to the triceps area of the same arm. All these sensors are wired to a SPHERE (Sensor Platform for HEalthcare in a Residential Environment)[1] module ⓐ which is a wireless wearable platform having built-in gyroscopes and accelerometer for activity recognition and a wireless connectivity using Bluetooth Smart (Fafoutis et al., 2017). PPG ⓓ, EDA ⓔ and EMG ⓕ sensors produce analogue outputs and are connected to a 4-channel A/D (Analog to Digital) converter ⓒ allowing the SPHERE module to sample the readings at 100Hz. SKT sensor ⓑ, due to the small variation (less than 1 degree centigrade), is connected directly to the SPHERE module through I2C (Inter-Integrated Circuit) bus and sampled at the same rate. Data sampling at 100Hz is sent as a notification package of 20 bytes in length including all 4 sensor data readings when the SPHERE module is connected and subscribed by a BLE client which, in this case, is an Android smartphone. All wearable sensors using in the *emotionWear* sensing glove are common off-the-shelf biomedical sensors, and the

[1] http://www.irc-sphere.ac.uk

details for the sensors are listed in appendix A.

(ii) Android Smart Phone

An Android smartphone (model: Google Pixel with Android OS version 7.1.2) with tailor-made application software acts as a central control in the *emotionWear* framework. The application software comprises four different modules: ⓖ allows manual selection of multimedia contents previously downloaded to a particular folder as separate files and display as two images on the smartphone's screen such that when wearing a VR headset, the user sees a 2-Dimensional image presented to each eye. Audio content is applied through an earphone, therefore, the subject can be treated as being isolated from the outside world and focussed only on the multimedia contents. ⓗ During the multimedia playback, the corresponding signals measured by the wearable biosensors in (i) are collected through the BLE connection and saved to a file. ⓚ The ambient sound is kept to a minimum during the study, and audio from the surrounding is picked up by the smartphone's built-in microphone to record any sound generated by the subject during the test. ⓜ Once a study session is over, the smartphone pushes the related data files (i.e. biosignals and the context) to the Internet through WiFi or cellular and stored in the cloud ⓝ.

(iii) Data Analysis

Data analysis is done using iPython, based on the jupyter notebook application[2] which has an active community providing third-party libraries for data sciences (Shen, 2014). The iPython code is written to show a dashboard view of the *emotionWear* framework for analysing the synchronised stimulation (i.e. the multimedia contents including visual and audio) and the accompanying physiological responses (i.e. the signals picked up by the 4 wearable biosensors, together with the capture of the environmental sound) under emotional promotions. The visual stimulus is displayed as still images which are the screen shots of the video in 100ms interval ⓞ, the audio part of the video is displayed as an amplitude envelope plot ⓟ, the capture of the environmental sound generated from the subject during study is also plotted in the same scale ⓠ, a set of interactive control widgets of ipywidgets[3] are implemented to move the dashboard view to the specific time instances according to the following criteria:

[2] http://www.jupyter.org
[3] https://ipywidgets.readthedocs.io/en/stable/

- Slider: slide to anywhere on the time scale in 100ms interval, and the corresponding stimulus (video screen shot and audio segments) and responses (waveforms of the biosignals) at the selected time instance are displayed.
- Threshold level detection for the four biosignals activate the comparison logic for small, medium and high threshold amplitudes preset by the program. Once the comparison output is positive, the slider is moved to the time instance of the comparison.
- Threshold level detection for autonomic specificity activates the comparison logic for ANS patterns comprising the four biosignals preset by the program. Once the comparison output is positive, the slider is moved to the time instance of the comparison.

The actual waveforms for the corresponding biosignals in the time and frequency domains are displayed in ⓣ. These waveforms show the biosignals being sampled at 100Hz synchronised with the multimedia stimuli in ⓞ ⓟ, and the sound capture ⓠ.

6.3.2 Biosensors and Features Selection

Innervations happen to many human organs during an emotional physiological response (Figure 6.1 shows some examples), but non-invasive measurements cannot be conveniently applied to most of them. Researchers normally focus on the following four types of wearable biosensors due to i) non-invasive, ii) easily available, iii) mature technologies for manufacturing and analysing, and we have also chosen them for the present study. Additionally, the feature extraction process requires special consideration according to the nature of emotional stimuli.

(a) PPG, EDA and SKT

PPG captures the blood volume pulses which can then be used to derive features from both time and frequency domains. EDA captures the skin conductance and both the mean and standard deviation are extracted as features. Similar to EDA, SKT captures fingertip temperature with features derived from both mean and standard deviation. Table 6.1 lists all features with the associated calculations.

All features are calculated based on different rolling windows defined by the "window" parameters which affect the resolution for temporal analysis. A short window

TABLE 6.1: Feature Extraction from PPG, EDA and SKT sensors

PPG Features	**Calculations based on Python (import numpy, pandas and scipy)**
IBI	Peak detection of raw PPG signal and get an array (ppgnn) Interbeat Interval (IBI) = ppgnn.interpolate(method='cubic')
HR	Heart Rate = (60 second × sampling frequency) / peak-to-peak duration HR = IBI.rolling(window, min_periods = 1, center = True).mean()
SDNN	Standard deviation of IBI SDNN = IBI.rolling(window, min_periods = 1, center = True).std()
SDSD	Standard deviation of the difference between adjacent ppgnn ppgdiff = pd.DataFrame(np.abs(np.ediff1d(ppgnn))) ppgdiff = ppgdiff.interpolate(method='cubic') SDSD = ppgdiff.rolling(window, min_periods = 1, center = True).std()
RMSSD	Root Mean Square of the difference between adjacent ppgnn ppgsqdiff = pd.DataFrame(np.power(np.ediff1d(ppgnn), 2)) ppgsqdiff = ppgsqdiff.interpolate(method='cubic') RMSSD = np.sqrt(ppgsqdiff.rolling(window, min_periods = 1, center = True).mean())
SDNN/RMSSD	Ratio between SDNN and RMSSD SDNN_RMSSD = SDNN / RMSSD
LF	Power Spectral Density (PSD) for low frequency range (0.04Hz to 0.15Hz) Y = np.fft.fft(IBI)/window, Y = Y[range(window//2)] LF = np.trapz(np.abs(Y[(freq>=0.04) & (freq<=0.15)]))
HF	PSD for high frequency range (0.16Hz to 0.4Hz) HF = np.trapz(np.abs(Y[(freq>=0.15) & (freq<=0.4)]))
LF/HF	PSD ratio between LF and HF LHF = LF / HF
EDA Features	**Calculations based on Python (import numpy, pandas and scipy)**
EDA(filtered)	eda = raw EDA signal sampling at 100ms B, A = signal.butter(2, 0.005, output='ba') EDAf = signal.filtfilt(B, A, eda)
EDA(mean)	Getting rolling mean of filtered EDA raw signal (EDAf) EDAmean = EDAf.rolling(window, min_periods = 1, center = True).mean()
EDA(std)	Getting rolling standard deviation of filtered EDA raw signal (EDAf) EDAstd = EDAf.rolling(window, min_periods = 1, center = True).std()
SKT Features	**Calculations based on Python (import numpy, pandas and scipy)**
SKT(filtered)	skt = raw SKT signal sampling at 100ms B, A = signal.butter(2, 0.005, output='ba') SKTf = signal.filtfilt(B, A, skt)
SKT(mean)	Getting rolling mean of filtered SKT raw signal (SKTf) SKTmean = SKTf.rolling(window, min_periods = 1, center = True).mean()
SKT(std)	Getting rolling standard deviation of filtered SKT raw signal (SKTf) SKTstd = SKTf.rolling(window, min_periods = 1, center = True).std()

such as 10 seconds is applied for most of the time domain features, but it is not reliable for frequency domain features especially Low Frequency (LF) (0.04Hz to 0.15Hz) (Heathers, 2014). While there are obvious variations in the High Frequency (HF) features, the LF features are not stable since a frequency transform on low frequency components is not reliable due to insufficient data over a short time frame, e.g. a period of 25 seconds is required for one cycle of 0.04Hz signal in LF. For normal film watching as well as real time situations, emotional scenes are usually very short compared to a 5 minutes rule in medical cardiac evaluation (Camm et al., 1996; Sassi et al., 2015).

(b) EMG

EMG indicates the degree of muscle contraction. Ekman has demonstrated that facial muscle contraction is a concomitant to autonomic specificity such that a motor program is initiated and generates specific facial expression (Ekman, 1993). Other than facial muscles, skeletal muscles of body parts are also studied by different researchers showing a system of emotional muscle response termed BCAS (Body Action Coding System) (Huis in 't Veld, Van Boxtel and Gelder, 2014; Huis In 't Veld, Van Boxtel and Gelder, 2014). However, there is not much empirical research supporting this system on emotion recognition. Facial expression detection may not be easily applied to a wearable sensor, so EMG in this study has been placed on forearm, biceps and triceps but no significant relationship between these signals on those areas could be found. Finally the EMG data was discarded in the current study.

6.3.3 Stimulation of Emotions

Visual cues are common and successful stimuli for emotion elicitation. Still images and film clips are traditional visual and audiovisual cues used in academic research to elicit specific emotions with standardised materials provided by different academic institutions for easy referencing, for example International Affective Picture System (IAPS) (Lang, 1995; Lang and Bradley, 2007; Lang, Bradley and Cuthbert, 2008) from University of Florida and emotional film clips proposed by Gross and Levenson (Gross and Levenson, 1995) and Schaefer et al. (Schaefer et al., 2010). However, the effectiveness of these two types of visual stimuli for emotion elicitation is still debatable (Uhrig et al., 2016). Still images seem to be less complex for investigation of single affective states (Lang and Bradley, 2007), but emotional films may be higher in ecological validity (Gross and Levenson, 1995). Therefore, both still images and film clips are adopted in the current study. Selected pictures from IAPS are compiled as a slide show with 6 seconds displaying the picture and 20 seconds blank screen between pictures, and the selection criterion is based on the highest and lowest valence from the accompanying test report inside the IAPS package (file "AllSubjects_1-20" inside folder "IAPS Tech Report"). These slide shows are stored as film clips in mpeg layer-4 format (.mp4) without auditory content. Film clips (Gross and Levenson, 1995; Schaefer et al., 2010) with the highest ranking or hit-rate were used as normal mp4 multimedia files with both visual and auditory contents. Converting picture slide shows into film clips allows both types of visual stimuli to share the same functions in the *emotionWear* framework. Table 6.2 lists the pictures (identified by the individual reference numbers in IAPS) and the film clips used to elicit the five basic emotions under study.

TABLE 6.2: Elicitation of basic emotions using referenced stimuli.

Emotions	**Pictures (Numbers Refer to IAPS Database (Lang, Bradley and Cuthbert, 2008))**	**Film Clips (Names and Duration of Film Clips Refer to Schaefer et al. (Schaefer et al., 2010)) and the bracketed numbers refer to different clips of the same movie**
Happiness/Joy	High valence rating: #1710 (Puppies), #1750 (Bunnies), #5833 (Beach), #1460 (Kitten), #2050 (Baby), #1440 (Seal), #2040 (Baby), #2070 (Baby), #8190 (Skier), #2080 (Babies)	(1) Something About Mary [2] (2) A fish called Wanda (3) When Harry met Sally
Anger		(1) Schindler's list [2] (2) Sleepers (3) Leaving Las Vegas
Fear	Low valence rating: #3053 (BurnVictim), #3102 (BurnVictim), #3000 (Mutilation), #3064 (Mutilation), #3170 (BabyTumor), #3080 (Mutilation), #3063 (Mutilation), #9410 (Soldier), #3131 (Mutilation), #3015 (Accident)	(1) The Blair Witch Project (2) The Shining (3) Misery
Disgust		(1) Trainspotting [2] (2) Seven [3] (3) Hellraiser
Sadness		(1) City of angels (2) Dangerous mind (3) Philadelphia

A longer film, around 30 minutes, was chosen as the audiovisual stimuli for continuous elicitation as an extension of the test for real time emotion recognition. A commercial TV drama program "Friends, season 2, episode 1 from NBC"[4] is targeted for "Joy" and this film has several moments of "Joy" emotion.

[4] https://www.youtube.com/watch?v=ydQ26w2TVEE&list=ELVOi8oFxJzT0

6.3.4 Procedures

Each subject is briefed on the project and experiment by the investigator explaining the details listed on the "Information Sheet for Participants". The investigator completes the questionnaire and collects basic details of participants (such as age range, sex, etc.) according to the "Questionnaire" form. The investigator also explains the potential risks of emotional harm from watching irritating materials especially those eliciting fear, disgust and anger emotions. Participants can refuse to watch those materials if they feel uncomfortable, thus the investigator will only select and show to the participants the appropriate visual stimuli. The investigator helps to choose one film clip from each emotion category for the study and the IAPS slide show under the participant's agreement. The maximum duration for the film clips is less than 6 minutes, and the slide show is 9 minutes, plus the handling time between switching media, and the total study period is less than 1 hour. The subject wears a VR headset with an Android smartphone installed inside the headset to show the emotional films and collect data from the wearable sensors through Bluetooth wireless connection. The subject may need to adjust the focus on the VR headset in order to get a clear picture according to the instructions from the investigator. The investigator will help the subject to wear a glove with the wearable sensors installed, and the sensors are wirelessly connected and controlled by the Android smartphone in the VR headset. The investigator will need to make sure all wearable sensors are properly installed and the biomedical signals picked up are at the highest quality. Three minutes are reserved to allow the subject to relax and at the same time, the baseline signals are collected to adjust the experimental data. The experiment will then start after the relax period, and the film watching and data collection are performed automatically. When the experiment stops, the investigator will help the subject to remove the sensors and the VR headset. The investigator will continue filling in the unfinished questionnaire and collect subjective feelings from the subject based on the Self-Assessment Manikin (SAM) form from the IAPS package. The experiment ends, and the subject can collect the "Information Sheet for Participants", which shows the contact information if required for future communication.

6.4 Results

After a successful elicitation of emotions, the perception promotes physiological responses, which enable wearable sensors to perform biomedical measurements if the variations of the corresponding biosignals are within the limits of contemporary sensing technologies. Machine learning enables statistical prediction of emotions based on supervised learning of features extracted from a large database of physiological data with ground-truth labels according to previous research (Kim and André, 2008; Godin et al., 2015; He, Yao and Ye, 2017). Our result applies autonomic specificity using the minimum number of biological variables for emotion recognition through simple feature comparison proposed by previous empirical studies (Kreibig, 2010; Levenson, Ekman and Friesen, 1990; Levenson, 1992). The method can be effortlessly used in other areas requiring emotion recognition as an integral part of the whole system, especially those resource-limited smart sensors used in the IoT world. Three types of common biosensors (since EMG was discarded) that can be easily purchased are selected for the current research, so our result is repeatable with contemporary technology. All raw data files have been processed with different data analysis tools presented in Chapter 5 section 5.6, and the final data in graphical form for each participant are illustrated in Appendix D. The following subsections present the Response-Stimulus Synchronisation (RSS) results of the *emotionWear* framework using the three different types of audiovisual stimuli dedicated to specific purposes:

(a) Still pictures:

This visual stimulus contained 20 still pictures without auditory content, thus a relatively simple attention to the perception process was established. The pictures were separated into two groups with similar valence ratings within each group, but high valence contrast between the groups. RSS results showed the responses of all participants during the viewing of individual pictures for high and low valence, as well as the switching of pictures within-groups and between-groups.

(b) Short film clips:

Film clips with dedicated emotional rankings and short durations (see Table 6.2) stimulated specific perceived emotions in participants, and the purposes of using RSS were

(i) validation of emotion elicitation, (ii) comparison between perceived and felt emotions and (iii) pattern matching of biosignals with ANS specificity for successful and unsuccessful emotion elicitations.

(c) Longer version film clip:

A longer film clip around 30 min with multiple emotional stimulation moments of "joy" caught viewers' attention and elicited corresponding emotions, and the RSS demonstrated the whole stimulation, attention, perception and autonomic responses process. Additionally, synchronisation was extended to the environmental context by demonstrating how the collected background sound was synchronised with the physiological responses during the emotional perceptions.

6.4.1 Still Pictures

Twenty still pictures were chosen from the IAPS's database of 1182 photos; the first group of 10 was selected with the highest valence rating and the second group of 10 for having the lowest values; thus, a maximum contrast in emotional valence was established between the two sets of picture stimuli (the ratings are found from the IAPS technical report (Lang, Bradley and Cuthbert, 2008) inside the IAPS package). The selected pictures were displayed in sequence according to Section 6.3; half of them were rated as high valence, which normally stimulate positive emotions such as happy, content or pleased; another half with a low rating should produce negative emotions such as distress, sadness or frustration. Each still picture was displayed for 6 seconds and was followed by a blank screen of 20 seconds; thus, a total of 20 $\times$ (20 seconds + 6 seconds) = 520 seconds was spent to complete one experiment for a sequence of 20 images. All subjects (100%) experienced an unpleasant emotion after switching to the negative valence picture group, and they all expressed the "disgust" emotion during the subjective feeling survey. Figure 6.3 shows two typical physiological responses from the wearable biosensors of the subjects watching the two categories of still pictures in sequence according to the timing shown in the horizontal axis.

A significant increase in EDA response was found during the switching from positive to extreme negative valence stimulus when the unpleasant picture group was displayed, as

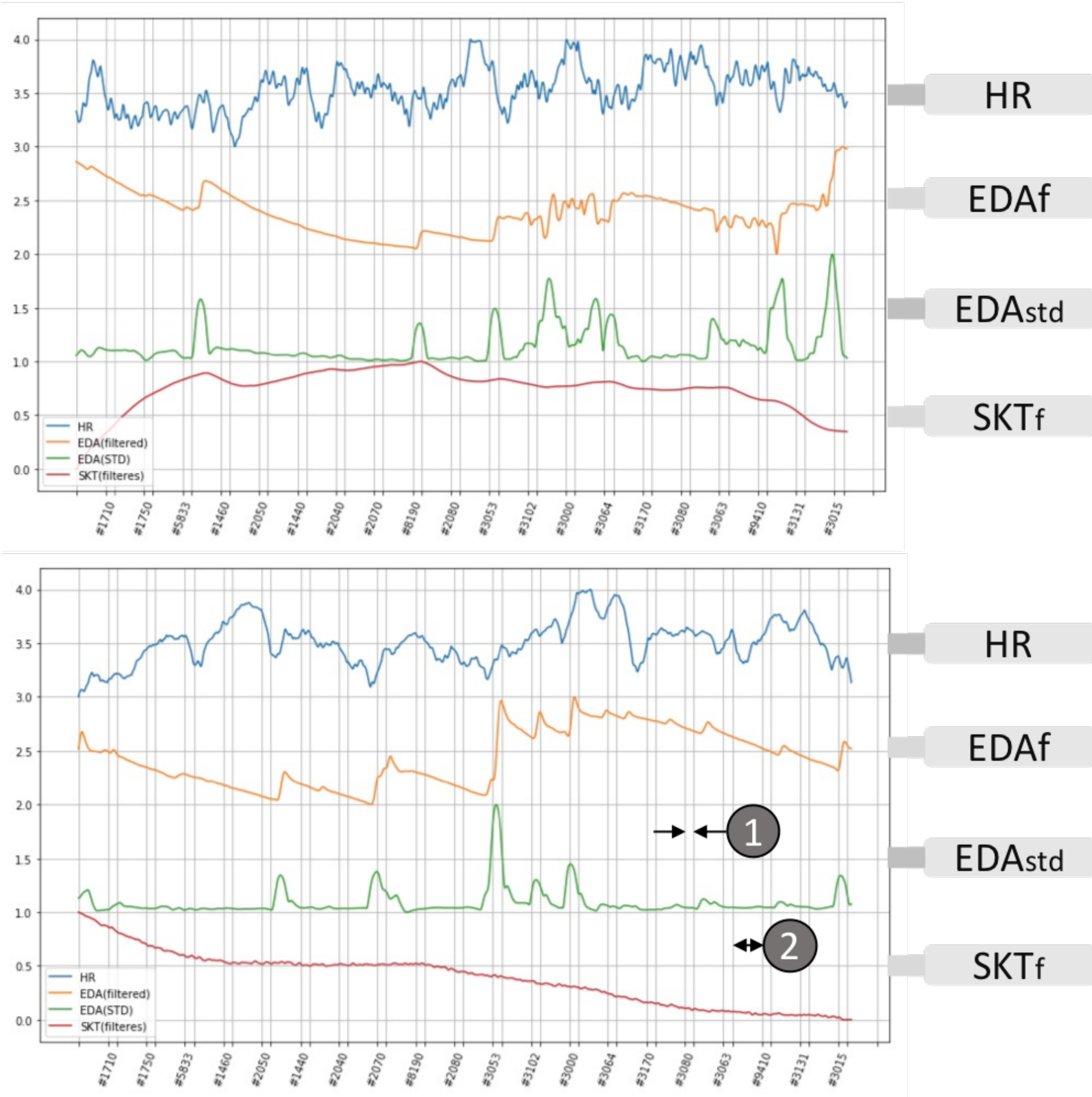

FIGURE 6.3: Physiological responses for still picture stimuli (IAPS). Each study session of emotion recognition using IAPS stimuli lasts a total of 520s; the 20 chosen pictures in two categories listed in Table 6.2 are shown as still images on the display in sequence of six seconds per image ①, and the gaps between images are each filled with a 20s black screen ②. The x-axis shows the arrangement of the two categories of IAPS pictures according to their unique reference numbers. All participants showed unpleasant emotion when the first negative valence picture was displayed (#3053). The upper picture extracted from participant EP6 (appendix D) shows a higher heart rate deceleration during the switching of emotional valence, and the lower picture extracted from participant EP1 (appendix D) depicts a more significant skin conductance change.

well as a moderate increase in the average heart rate, and simultaneously the fingertip temperature started to drop until the end of the study. Picture #3053 is the first unpleasant picture in the sequence, and all changes started from that moment. A significant change in skin conductance and a heart rate deceleration occurred at picture #3053 and also other moments switching to new pictures. However, not all of the switching of pictures, especially the high emotional valence pictures, caused the hypothesised OR activities, which illustrated the different initiation of the orienting response process, and the individual perception differences were demonstrated among the 10 subjects. A combination of an average increase in heart rate and skin conductance, together with a decrease in fingertip temperature agrees with those reported by Kreibig (2010) for the basic emotion of "disgust (mutilation)".

Previous research has shown that EDA seems to be the only reliable and consistent phasic OR indicator (MacDonald and Barry, 2017). If the focus is diverted to EDA only, then pleasant emotional pictures (i.e., cute animals and babies) give less response, but unpleasant pictures stimulate more emotional perceptions. Additionally, the OR occurrences for subsequent unpleasant emotions keep reoccurring with increased delay from the emotional scenes after the initial response due to the audiovisual stimulations. The after study survey shows that the participants felt neutral to most of the selected high valence pictures, but perceived "disgust" and "fear" emotional states during the viewing of those low valence pictures.

6.4.2 Short Film Clips

Film clips using in this study were rated and classified by Schaefer et al. (2010) and some films were also investigated by Gross and Levenson (1995). All film clips were downloaded from related web site[5] mentioned in the article. Section 6.3 describes the 15 film clips in five categories that have been used as audiovisual stimuli for eliciting the five discrete emotions under the current study, and the results are summarised in table 6.3.

TABLE 6.3: Film clips elicitation analysis

Film clips target emotions (and distribution)	Emotion (target = subjective)	Emotion elicitation (subjective)	Emotion elicitation (measure)	Hit-rate (measure = subjective)	Subjective arousal (average)	Subjective valence (average)
Joy (19%)	100%	19%	12%	60%	3.50	3.75
Anger (23%)	0%	0%	4%	0%	0.00	0.00
Fear (15%)	43%	27%	12%	43%	5.43	7.43
Disgust (21%)	71%	26%	19%	57%	5.57	8.14
Sadness (23%)	57%	18%	7%	43%	4.20	7.14

The 10 subjects were allowed to choose the type of emotional film clips since some of them were uncomfortable to certain type of emotional films especially those with scary and

[5] http://www.ipsp.ucl.ac.be/FilmStim/

disgusting scenes. No question was asked to identify repeated exposure to films they had previously watched since this was part of the current study. Finally, a total of 48 film clips were used for this study, and only half of them could successfully elicit emotions. Table 6.4 shows the reasons of unsuccessful elicitation from the after study survey with the subjects when they could express their subjective feeling of the film clips they have watched. Most common reason seems to be insufficient watching time to initiate an emotion, particularly those emotions related to "anger" and "sadness". The next common reason is that the subjects could not feel the target emotions or even any emotion at all; this happened on all categories but "anger" is the worst with zero subjective elicitation. Repetitive exposure seems not as bad as we have anticipated since almost half of the films have been watched by the participants, but most of them could still perceive the target emotions especially those related to "fear" and "disgust".

TABLE 6.4: Reasons for unsuccessful emotion elicitation

Reasons for unsuccessful emotion elicitation	Percentage
Saw the film clip before (many times)	17%
Film clip too short	42%
Cannot understand the language	4%
Didn't feel the target emotion	33%
Others	4%

Table 6.3 also shows that subjective feeling agrees with the target emotions on "joy" since the scenes are easily identifiable although the subjects may not perceive the same emotion for most of the "joy" film clips. No subject agrees on "anger" emotion and this matches with previous research that anger emotion is hard to elicit in film watching (Zupan and Babbage, 2017). "Fear" and "disgust" are hard to distinguish for most of the subjects and this phenomenon matches with previous studies indicating that "disgust" sometimes comes with "fear" emotion. The percentage of subjective feeling of emotion elicitation and the actual elicitation by measurement is also listed in the table, which reveals that there is no emotional perception even the subjects have claimed the target responses on the film clips, especially those with low arousal levels.

OR analysis was used to validate the recognition of the emotional responses by checking the HR deceleration for two seconds starting one second before the change of EDA response, and we have achieved around 80% accuracy for predicting a valid emotional promotion, figure 6.4 depicts typical waveforms showing the HR and EDA responses for successful and unsuccessful emotion elicitation.

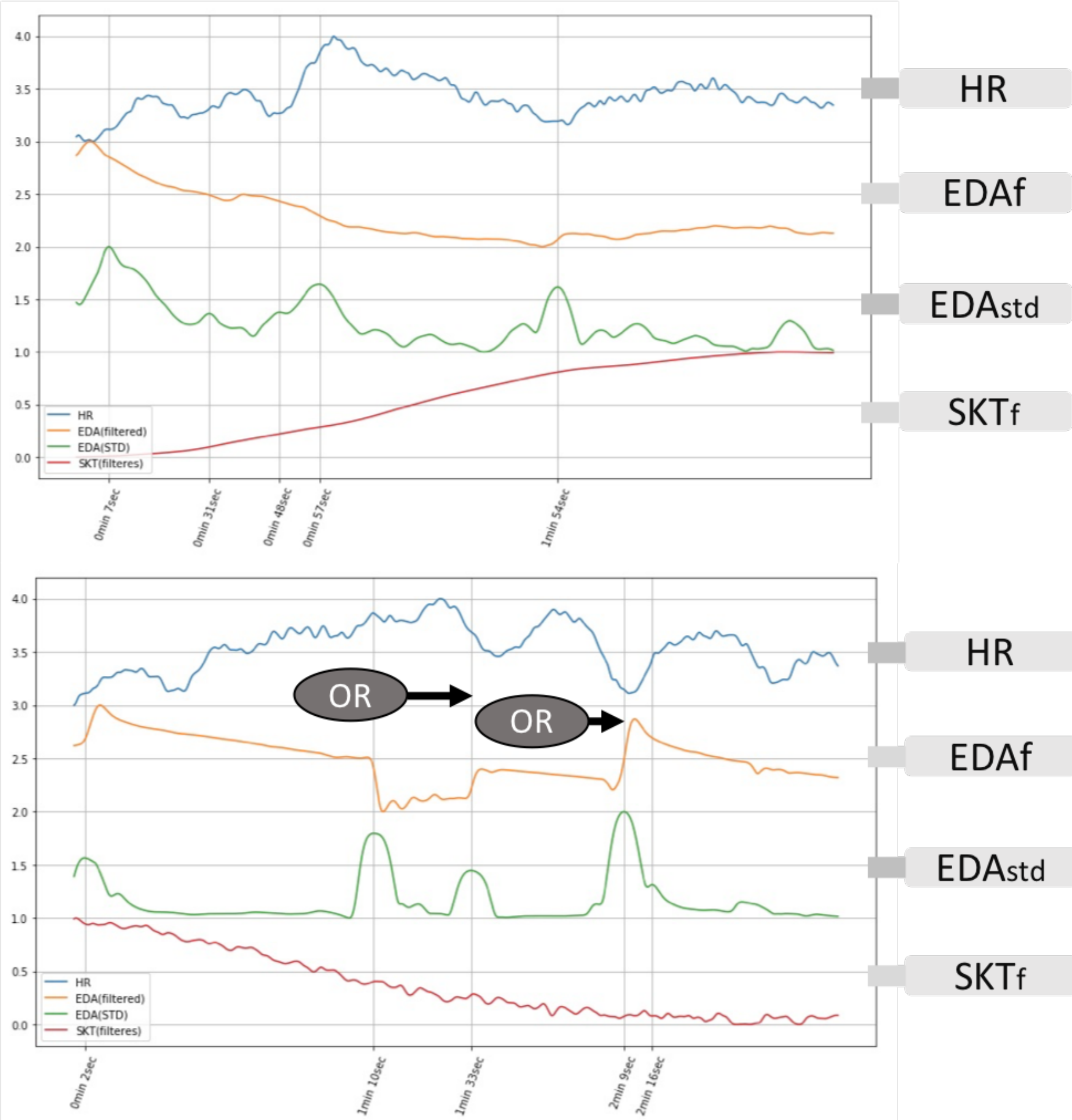

FIGURE 6.4: Orienting Responses on Unsuccessful (upper graph from test 22) and Successful (lower graph from test 21) Emotion Elicitation on Film Clips, refer to Appendix D for test numbers

After validating a successful emotion elicitation, the average levels for the three biosignals (HR, EDA and SKT) after an occurrence of OR were calculated and compared with the autonomic specificity patterns (Figure 6.1), and we obtained a reasonable accuracy of emotion prediction. Table 6.5 shows the confidence power of emotion recognition before and after the moment of OR (i.e. the assumption of successful emotion elicitation). The calculation was based on a 60 seconds interval after the OR moment for a successful emotion elicitation, and the other one was calculated using the whole film duration and segmented into

60 seconds interval then take the average. All three variables showed a significant increase in the confidence level representing by the p-value, and the results of EDA and SKT met the criterion for statistical significance ($p < 0.05$). The HR feature is a more complicated variable affecting simultaneously by both branches of the ANS, so a more sophisticated pattern must be investigated to increase the recognition accuracy. Validating the emotion elicitation moment seems to be critical in choosing the averaging interval for recognition.

TABLE 6.5: Emotion recognition before and after validation of emotion elicitation

Biosignal	Responses match with ANS specificity before successful emotion elicitation	Responses match with ANS specificity after successful emotion elicitation
HR	$p < 0.992$	$p < 0.126$
EDA	$p < 0.989$	$p < 0.042$
SKT	$p < 0.362$	$p < 0.036$

Due to the lack of experience in the statistical significance test, the sample size was not properly defined during the planning stage. Even the p-values seemed to match with the confidence level for statistical significance (i.e. < 0.05), the power for this statistical test was still not good enough to reject the null hypothesis (Anderson, Kelley and Maxwell, 2017). Based on the power analysis algorithm, table 6.6 depicts the calculation results for minimum sample sizes using the Python codes presented in Chapter 5 section 5.6 (*iPython codebox: minimum sample size calculation*). The current sample size is only 15, thus, the calculated p-values for the limited number of data indicate that there are significant differences for the results before and after the occurrence of OR but the reliability and reproducibility of the results may not be agreed until the sample size reaches around 100.

TABLE 6.6: Minimum sample sizes from power analysis calculation

Biosignal	Effect size	Confidence level	Power (1 - p-value)	Minimum sample size
HR	0.539	0.05	0.874	96.8
EDA	0.866	0.05	0.958	90.8
SKT	0.793	0.05	0.964	58.7

6.4.3 Longer Version Film Clip

A longer film (a TV program around 30 minutes) was used to extend the existing test to analyse the physiological responses captured by the current emotion recognition framework.

The result verifies the detection of OR activities as validation of successful emotion elicitation and reviews the effectiveness of the recognition method using a comparison with ANS specificity patterns (average high in HR, EDA and SKT). A "joy" emotional film (TV program: Friends) having multiple and continuous emotion elicitation moments has elicited "joy" emotion with high arousal and high valence levels. Figure 6.5 shows the biosensor responses for continuous emotion elicitation; 13 out of 14 OR activities happen exactly at the moments of the scenes eliciting the "joy" emotion (marked by vertical lines on the graph), only the first moment (marked as X in the upper graph) showing a false detection of OR. A validation on the "joy" emotional moments was further enhanced by the recording of the surrounding sound when viewing the film, and all related OR moments were accompanied by a subtle laughing sound of the subjects (see lower graph of Figure 6.5). Interestingly, there is no delay in the phasic OR synchronised with the joyful scenes similar to the still pictures experiment (see Section 6.4.1). However, it is likely to be a significant challenge to automatically identify the subject's laughs from the complicated ambient sounds in real life.

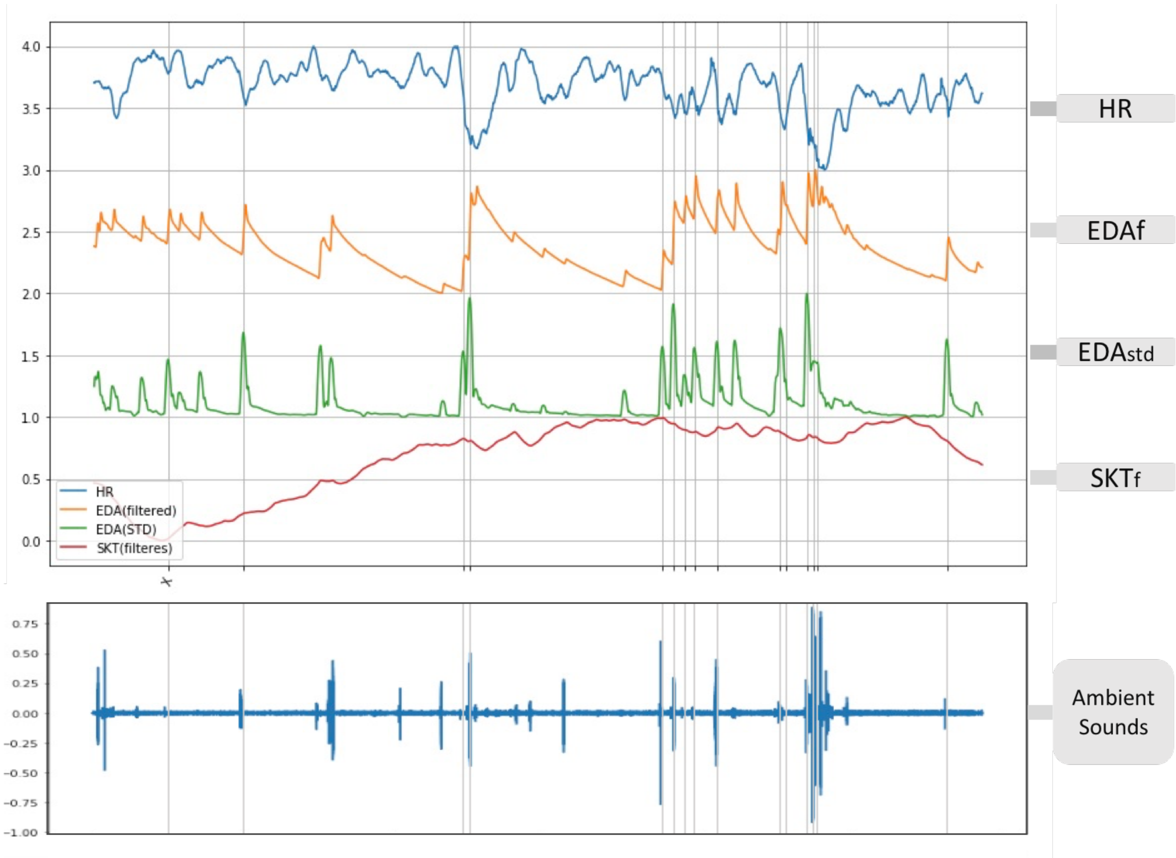

FIGURE 6.5: Physiological Responses for Continuous Emotion Elicitations (data extracted from participant EP1 - Appendix D)

6.5 Discussions

The present study has investigated three areas of emotion recognition based on physiological responses. Firstly, a proposal of a complete emotion recognition system *emotionWear* using affordable and readily available technologies was investigated that could synchronise between stimulation and the corresponding physiological responses. Our hypothesis is that synchronisation between system input and output can elucidate the relationship between emotional stimulation and the associated physiological variations. The collection of emotional pictures and film clips is easy to control in terms of stimulation timing. Synchronisation between stimuli and the corresponding responses is extremely helpful in analysing the effectiveness of a recognition method or device such as an individual biosensor. The framework *emotionWear* was designed and implemented from scratch to meet this purpose. The present research has used part of the functions of this emotion recognition analysing framework, which can be expanded: (1) to include all kinds of natural stimuli such as visual, auditory, haptic, olfactory and gustatory stimuli; (2) to capture the context during the study such as surrounding sounds and activities of the subjects; and (3) to monitor the physiological responses of the subject including all types of biomedical sensing data collected from available biosensors. The data analysis capability of *emotionWear* using jupyter notebook based mainly on Python has been proven to be a convenient tool for viewing both stimulation and emotional responses at the same time.

Based on the *emotionWear* framework, the second investigation focuses on the validation of a successful emotion elicitation, which enables a ground-truth database for emotion recognition using signal levels' comparison or machine learning. The onset of OR activities is hypothesised to be an indicator for human attention and the initiation of the internal perception process (Graham and Clifton, 1966; Bradley, Keil and Lang, 2012); thus, we want to illustrate this OR activity during emotion recognition from *emotionWear*. A successful emotion elicitation is critical for enabling an accurate recognition especially in statistical prediction methods during both the training/testing and application phases. OR activities are hypothesised as the registry of sensory intake preparing the human (and animal) body to react to the changing environment due to novel stimuli. Numerous empirical studies have proven that the concomitant biological indicators (e.g., cardiac deceleration, skin conductance changes, pupil dilation) are associated with the initiation of the OR process. HR deceleration and rapid onset of EDA are being monitored in our framework validating a successful elicitation of emotions, and the results of our practical experiments agree with the hypothesis that the OR process is initiated when the stimuli (i.e., novel pictures and film clips that are significant to the participants) are applied to the subjects. The OR activities based on HR and EDA signals enable our framework to capture the emotional responses after the perception. However, according to the hypothesis, defensive response will be perceived during aversive stimuli, which causes HR acceleration instead. Therefore, different algorithms must be implemented in validating the emotion elicitation process, especially for humans with specific phobias.

The final investigation considers the coverage of emotion recognition using common off-the-shelf biosensors. Many previous empirical research works have hypothesised and proven to get high recognition accuracy using the three biosensors similar to the current study. We believe that each biosensor may have their individual irreplaceable feature in the recognition process. The OR process is indicated by sudden variations of skin conductance when novel stimulations are applied, and still pictures, short film clips and the longer film with multiple stimulations can verify this behaviour. However, a non-specific response happens at other moments not related to any specific stimulations, and this is a normal physiological response for humans (Cacioppo, Tassinary and G. Berntson, 2007). EDA variations are concomitant to emotional arousal; thus, it is a common variable for autonomic specificity. Similar to EDA , HR deceleration is also an OR indicator illustrating the onset of the perception process. Again, the two branches of ANS are continuously innervating the cardiac acceleration and deceleration to support other physiological activities balancing the human biological systems. Therefore, the monitoring of both EDA and HR variation simultaneously gains a better estimation of OR activities. According to ANS specificity research, fingertip temperature helps to differentiate pleasant and unpleasant emotions, and our result has also demonstrated this response (see Table 6.5). The current study has also illustrated the possibility of emotion recognition with the level comparison method using only these three biosensors (i.e., PPG , EDA and SKT). The basic assumption is that a set of biosignals can be collected from a specific interval after a successful emotion elicitation process.

Theoretical cognitive research in attention and emotion is still in its infancy, and there are many questions waiting to be answered in the whole attentional processing of the environmental emotional stimuli (Yiend, 2010). OR is the next step after a selective attentional process, which is a highly complicated mechanism under extensive research and is showing extremely different attentional effects according to individuals with various physical and mental conditions (Samanez-Larkin et al., 2014; Yiend et al., 2015). However, the identification of the OR processes enables a way to capture the necessary environmental context of stimuli ready for the corresponding scientific methods to extract the primal components of stimulation.

Further expansion of this work is required to gain better understanding of the relationship between OR activities and emotion elicitations. The timing of cardiac deceleration, the duration of deceleration, the possible cardiac acceleration for subject-dependent phobia response and the spatial relationship between HR and EDA are critical variables for emotion recognition based on physiological responses. More data should be collected from different subjects on single emotional type, as well as multiple emotions in order to build a better statistical model for prediction.

6.6 Conclusions and Future Works

An emotion prediction framework *emotionWear* has been proposed in this chapter for predicting human emotions based on common wearable biosensors. The framework's specific feature of synchronisation between emotional stimuli and the corresponding physiological responses enhances the data analysis of the coverage of emotional states from individual to a combination of biosensors. A novel algorithm based on the detection of the OR hypothesis has demonstrated the ability to validate a successful emotion elicitation through this synchronisation process. After a validation of successful emotion elicitation, the HR, EDA and SKT variations matched the ANS specificity by the accuracy confidence of HR: $p < 0.126$ (87.4%), EDA: $p < 0.042$ (95.8%) and SKT: $p < 0.036$ (96.4%). Due to the small sample size, these confidence levels may not reflect the true population and is only treated as a reference for future evaluation. Experiment with more samples must be done to meet the minimum sample sizes and properly reject the null hypothesis (see Chapter 5 section 5.6.5).

Emotion has been researched for more than a century for humans and animals. Knowledge about emotion, especially the functions of emotion, has been extensively studied by researchers clarifying the mystery in many areas. There are still numerous related questions waiting to be answered from academia and industry, but the current understanding of emotion should be able to transfer the know-how into commercial applications such as AI and IoT. Biomedical engineering plays a key role in translating psychophysiological research results into practice through technology and provides dedicated and advanced tools such as accurate emotion recognition and prediction. The current research has established a strong background for emotion prediction through an experimental framework that collects a dataset of physiological response patterns synchronising with the associated stimuli under a valid emotion elicitation. Individual response specificity is also illustrated in the current framework, which shows that different subjects may behave differently, and even if their emotional behaviours are similar, the moments of emotional perception may be quite different. The RSS method to detect the OR activities was demonstrated as a validation tool for successful emotion elicitation, and this detection of the moments leading to an emotional response is extremely helpful in IoT environments where the implementation of affective sensors is enabled. Once the physiological responses are verified as coming from a true emotional perception, a combination of simple biosignal levels can be used with reasonable accuracy for emotion recognition by comparing them with the ANS specificity patterns. Machine learning can further increase the accuracy by extracting more features from various biosensors. More research is needed in clarifying the different OR activities for common discrete emotions, since it is necessary to accurately validate the emotion recognition. A future study on the time delay after a successful emotion elicitation and the optimum period for collecting physiological signals is also important to increase the emotion recognition accuracy.

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Chapter 7

Discussions

The conceptual framework for an artificial human sixth sense system seems to be possible according to a latest literature search (refers to section 2.4 in chapter 2), but not all required technologies are readily available for an immediate implementation especially the synchronisation between attention and emotion. The basic infrastructure for sensing anything anywhere has been established through the IoT, and the know how of human machine interaction is becoming mature enough for an intuitive computer interface through DUI's content communication between humans and machines. Psychophysiological research has provided empirically proven hypotheses enabling computer intelligence, such as machine learning, to predict human behaviours through emotion recognition algorithms. However, without knowing when to capture an emotional response, such as the sensing of a physiological variation on single or multiple bio-signals, the algorithms may not reliably reveal the perceived emotions. Current research has built a model showing one of the synchronisation technologies aligning the human attention with emotion as a proof of the hypothesis that a response-stimulus synchronisation is at least one of the missing piece for an artificial sixth sense system. Machine learning and other AI algorithms for predicting human emotion is a huge topic and is mentioned throughout the whole thesis, but the present study does not focus on how AI methodologies are utilised to perform the recognition or to enhance the accuracy. Alternatively, the target of the current research studies the missing technology empowering the collection of ground-truth datasets for machine learning, which is a core member of an artificial sixth sense system but is intentionally not included in the *emotionWear* framework in order to limit the scope of study and stay focus on the proposed hypothesis.

This chapter discusses further why the major technologies presented in previous chapters facilitate the implementation of an artificial sixth sense system, what specific concepts apply to build the *emotionWear* framework, and how the conclusion can be made from the experiment described in Chapter 5 proving the proposed hypothesis that response-stimulus synchronisation is the missing technology. Additional information and results from the experiment that have not been presented in the associated research paper (Chapter 6) are also discussed. The major technologies for an engineering implementation of an artificial sixth sense system based on the IoT may include the following items and they will be discussed in the coming sections:

a) Ubiquitous and Pervasive Computing

b) Disappearing Natural User Interfaces

c) Emotion Recognition

d) Emotional Response-Stimulus Synchronisation (RSS)

7.1 Ubiquitous and Pervasive Computing

Once the term "human sixth sense" is properly defined (see Chapter 2 section 2.1), the IoS concept based on the IoT appears to be a prefect solution for establishing an artificial sixth sense system. The major technologies to realise the system is the same as building an intelligent and smart home inside a smart city. Ubiquitous IP-connected sensors are the most critical components sensing the responses of an individual and acquiring the contents of an environment associated with the responses, i.e. the causes of the responses. Sensors connected with different protocols can be communicated with each others through a gateway or cloud integration, thus, a global sensing network is established where local and remote contexts can be compared. Cloud services are also the major ingredients in the IoS such that artificial intelligence can be applied to data collected from anywhere across the globe, and the data analysis can be used to predict the human behaviour in terms of discrete emotional states through emotion recognition algorithms.

IoT implements the concept of ubiquitous and pervasive computing described by Weiser (1991) linking unprecedented number of computers together on a single platform with universal communication standard: the TCP/IP. Smart devices, acting as the things in the IoT, are normally consisted of embedded network-enabled computers with various sensing and actuation capabilities, and interface with each other based on semantic technologies for effective M2M communications (Holler et al., 2014). According to Hui, Sherratt and Díaz-Sánchez (2017), technologies required for smart things to effectively function on the Internet allow things to communicate with one another under different communication protocols (the requirement of Heterogeneity), to roam freely in different system configuration (the requirement of Self Configurable), to dynamically feature upgrade according to situations (the requirement of Extensibility), to adapt easily to the changing environment (the requirement of Context Awareness), to astutely select mode of user interactions (the requirement of Usability), to exchange information safely (the requirement of Security and Privacy), and to provide bespoke services affectively (the requirement of Intelligence).

The IoS described in Chapter 2 section 2.3 combines network of sensors on the IoT platform where different types of sensors providing various functionality and sensitivity for diverse sensing applications. An artificial sixth sense system requires a server for individual sixth sense processing, and it can be a local server located in user's smart home or it can be a cloud based server for easy remote accessing. The sixth sense server will store all individual emotional events which include the causes and the results of every emotional instance. The causes and results may consist of the following components:

a) Stimuli

   The stimuli that stimulate the sensory system of the user will be captured and stored on the server, and these may include visual, auditory, haptic, olfactory and gustatory stimuli. The more types of stimuli that can be captured and stored on the server, the higher will be the recognition accuracy of the associated statistical pattern classification algorithm.

b) Environmental contexts

   The context or environment is also a part of the stimuli for the corresponding emotional responses, since lighting conditions, the activities that the user is performing, the weather of the environment may also be the Conditioned Stimuli for a particular emotional response (Watson and Rayner, 2000; Cagniard and Murphy, 2013).

c) Physiological responses

   Emotional responses, especially the physiological responses, may be the fingerprints of the different basic discrete emotional states. For non-invasive autonomic specificity, the features for emotional physiological responses may include heart rate, skin conductance, fingertip temperature, and muscle contractions, etc.

d) Subjective feedback

Machine learning may be used to identify the specific emotional states according to the autonomic specificity research, but a subjective feeling feedback from the users may also increase the prediction accuracy by self-labelling the training datasets. This feature may be optional and will assist the artificial sixth sense prediction especially at the beginning when training data is not enough (Hui, Sherratt and Díaz-Sánchez, 2017).

Once a selected classifier is properly trained by the chosen machine learning algorithm, it may then be use to predict the emotion states of the target users by inputting the remote or conceived stimuli. Thus, the sixth sense of a target user can be predicted by accessing this artificial sixth sense server. Each user will have a dedicated artificial sixth sense server acting as an individual sixth sense agent on the Internet.

However, the collection methodologies for emotional responses especially the physiological responses are not consistent from previous research. The validation of an emotional perception, the timing to collect the physiological signal variations, and the window widths for feature extraction are not obvious from a literature search in Chapter 2. Therefore, a technology to align the stimulation with the concomitant emotional response may be a solution to this problem, and this is treated as the missing technology which synchronises between attention and emotion. *emotionWear* is the tool to verify this missing technology hypothesis in the present study.

The design of *emotionWear* also followed the IoT concept integrating the necessary technologies into the assembly. However, the design didn't comply with all the seven requirements for building smart homes in smart cities since the *emotionWear* framework was not a complete artificial sixth sense system, its purpose was the verification of the proposed hypothesis that response-stimulus synchronisation was one of the missing technologies in building an artificial sixth sense system.

7.2 Disappearing Natural User Interfaces

The concept of DUI empowers a true NUI on the IoT (see Chapter 4) where HCI is performed intuitively as human nature. Interactions based on H2M and M2H technologies are established for information exchange based on contents, and the unnoticeable DUI allows conscious and unconscious communications with the human brains (Winkielman and Berridge, 2004; Tsuchiya and Adolphs, 2007; Smith and Lane, 2016).

Capturing emotional responses can be done by monitoring the physiological variables, such as facial expression, speech, and biosignals. A combination of different types of sensors from on-body, implanted and remote sensing may be a better choice for increasing the coverage and accuracy of monitoring but a dedicated algorithm for combining and synchronising the sensing results could be a challenge. Wearable sensors may be a better choice for continuous ambulatory sensing but the problem of motion artefact needs to be properly considered. The current study reveals the poor performance of the PPG sensor which has been seriously affected by minor unintended motions during the experiments. According to Chapter 5, autonomic specificity provides the groundwork for patterning the physiological variables with discrete emotion states, and the more types of bio-signals in the pattern matching the higher is the accuracy. However, it may still be able to make a coarse patterning using less number of bio-signal variables, for examples a stressful emotions using only EDA sensor, or distinguishing between distress and eustress by adding the fingertip temperature sensor.

The stimuli causing the emotional responses and the associated environmental context can also be captured by the IoS where those environmental sensors, such as cameras for visual images, microphones for auditory contents, accelerometer for vibration/haptic feedback, and the chemical sensors for olfactory and gustatory sensing. Context awareness technology (see Chapter 3) may help provide location awareness information for a coordinator (such as a smartphone) to initiate a capturing action of all related surrounding sensors to upload the sensing data to the sixth sense server. The experimental emotion recognition framework, the *emotionWear*, also implements a feature of collecting environmental sound as a verification of laughing during the watching of an amusement film clips (see Chapter 6 section 6.3).

Subjective feedback is optional at the initial stage when training dataset is not enough for a successful supervised learning process. Capturing of this feedback is relatively easier by asking question on user's smartphone to collect individual feeling of the previous emotional states detected. It may not be the best method since subjective feeling is usually not accurate (Gilbert, Gill and Wilson, 2002; Miloyan and Suddendorf, 2015), but it can help initialise the system at the beginning stage.

The concept of DUI is unnoticeable rather than invisible when human attention is concerned (Sá Cavalcante Schuback, 2006). Humans can be easily disturbed from unintended interference so methodologies should be adopted letting the test subjects to stay focused in a controlled environment. The design of the *emotionWear* was based on this idea of unnoticeable where the user interfaces would not interfere with the normal operations of the human subjects. Methods included the removal of all the physical wirings through a BLE connection, the assembling of all sensors and control module into a sensing glove, and the isolation from the environment during stimulation through the VR headset (see Chapter 5). There is plenty of room for improvement in the DUI implementation of the sensing glove design in order to keep the interfaces totally unnoticeable, for examples:

a) Miniaturisation

The original idea of the sensing glove design was an integration of all required sensors inside a wristband. Sourcing of miniaturised sensors, wireless module and power source that could fit in the limited area were the problems that couldn't be solved with the limited time and budget. However, the smaller the sensing device is, the better unnoticeable UI is achieved. An off-the-shelf sensing watch such as Apple Watch[1] or Fitbit[2] could be good alternatives but getting the raw data was not available for regular consumers or developers.

b) Remote sensing

Remote sensing such as RF leveraging can replace on-body sensing when related technologies are mature enough. Infrared imaging can detect body temperature from a distance but the precise measurement of a subtle temperature change on fingertips is still a challenge. Heart beat may also be detected through imaging but the skin conductance could be a bigger problem to be solved for remote sensing.

[1] https://developer.apple.com/watchos/
[2] https://dev.fitbit.com

c) Virtual Reality

The VR headset can isolate the wearers from the surrounding environment so the wearers can stay focused on the controlled audiovisual materials. Most participants of the experiment reported various degree of fatigue due to the heavy headset during the study, a light weight alternative is needed especially when a longer test is conducted. A dark room with big screen may be an option but the preparation requires more effort.

d) Integration of multiple sensors

A combination of wearable and remote sensing could be a better option which fully utilises the specific advantages of individual technologies. The *emotionWear* is able to combine sensors with different technologies and work together through the Android smartphone control and the wireless connectivity when only BLE and WLAN are used. A gateway is recommended when other wireless or wired sensors are integrated onto the platform, for examples, Zigbee or Z-Wave sensors.

7.3 Emotion Recognition

Emotion recognition has been extensively researched with theoretical and empirical evidence showing the concomitant physiological response patterns after an emotional perception for several discrete basic emotions (Ekman, 1992; Collet et al., 1997; Stephens, Christie and Friedman, 2010; Saarimäki et al., 2016; Ekman, 2016). Simple comparison of phasic or tonic differences on physiological variables enables a limited insight into autonomic specificity (Levenson, Ekman and Friesen, 1990; Kreibig, 2010), and machine learning based on univariate and multivariate analysis enables a more complicated pattern classification for getting a possibly better statistical prediction of emotion (Rani et al., 2006; Kragel and LaBar, 2014; Bulteel et al., 2014; Kapoor, 2014).

The capturing of the different types of physiological variables, and the feature extraction from the collected biosignals are common facilities for emotion recognition based on autonomic specificity. The experimental framework of the present research, the *emotionWear* (Chapter 5), has used only three biosensors with their tonic values feature-extracted for matching with the autonomic specificity that most researchers agree (Kreibig, 2010). The results show a high level of confidence in matching the empirical evidence from previous literature (see Chapter 6 section 6.4) after a validation of successful emotion perceptions, and it is believed that the using of more variables and a better recognition algorithm can boost up the accuracy further. However, the ground-truth labelling for training datasets is always a significant challenge (Constantine and Hajj, 2102), even the autonomic specificity listed in Kreibig (2010) using in this study also shows same pattern for both 'anger' and 'fear' emotions based on three variables only. Therefore, subjective feeling feedback is sometimes required for alleviating the problem of ambiguity between similar emotions when a better methodology is still not yet available. The timing for capturing the physiological variables, for examples, the moment to start the capture, the duration or window for continuous capturing, and the averaging window for the whole duration are not standardised for general emotion recognitions. The survey from Kreibig (2010) shows a wide range of common averaging window from half a second to five minutes, however, an emotion state may sometimes last for only a couple of seconds (see Figure 6.5). Thus, more research should be conducted for clarifying the timing parameters for emotion recognitions. Another area that seems to be insufficiently researched is the validation of emotion perceptions or the verification of successful emotion elicitation during the analysis of human stimulation to perception studies. Without knowing whether a subject has elicited a target emotion, the associated physiological responses may not be valid for further analysis. The technologies for synchronising the emotional stimuli and the corresponding responses may be a solution for the problems described above, and the next section will further discuss the related technologies.

Despite the fact that the five basic emotion states are generally agreed by most researchers studying emotion, there are still lots of controversial concepts, hypotheses, and theories in this field of study. The *emotionWear* framework has chosen to use the five basic discrete emotion states as the outcome from patterning with the autonomic specificity, since there are many formal empirical evidence from previous research for reference. However, criterion used by different researchers varied and only a rough comparison could be done using the summary table listed in Kreibig's paper. Furthermore, only four emotion states could be identified due to the restriction choosing consistent results from all reported research (see Chapter 5 section 5.3). Therefore, subtle differences might not be able to be identified due to their similarity such as fear and anger. There were participants expressed a subjective fear feeling after inducing a target anger emotion to them, however, physiological response based on the three bio-signals were not able to distinguish them. More bio-signals or more features from the signals could be a way to separate the two emotion states, however, more research must be done to verify this assumption. Signal strengths or the tonic levels of the bio-signals were not considered in the present study since there was no empirical evidence scientifically and systemically classifying the different emotions according to signal tonic quality.

This is well known that an emotional behaviour is personal and it not only differs by culture, but also varies according to individual history. Additionally, one's emotional behaviour may change when new experience is gained. The current study didn't go deep into the IRS effect on personal experience and the corresponding emotional response, each participant expressed individual feeling after exposing to predefined stimuli. However, the concept of artificial sixth sense system can keep track of individual emotional behavioural history which may tell why and when the change occurs.

The pattern matching method may be more effective using statistical prediction such as machine learning based on AI algorithm. However, machine learning was not in the scope of the current study due to the tight schedule for a PhD research. However, it may be a better method to increase the accuracy of emotion recognition on the *emotionWear* framework.

7.4 Emotional Response-Stimulus Synchronisation

IoS enables a continued sensing of the conditioned and unconditioned stimuli that stimulate an emotional perception of a subject in the IoT, but the problem is when exactly the sensing duration is related to a target emotional event? A machine learning algorithm empowers the prediction of user's emotions once the ground-truth dataset of stimuli is used to successfully train the classifier but the problem is how to validate that the stimuli are associated with the particular emotional perceptions? While the stimuli and the corresponding physiological variables are recognised as an emotional experience registered in the sixth sense server, which parts of the stimuli actually stimulate a specific emotional event for comparing with the future conceived and remote stimuli? The missing technologies for emotional response-stimulus synchronisation are hypothesised as a solution to the above problems. A study of attention and emotion in cognitive science seems to be highly relevant to this response-stimulus synchronisation but the associated technologies are not yet available for immediate application in real life.

Response-stimulus synchronisation also applies to research requiring similar technologies such as emotional lifelogging which captures day to day activities based on users' emotions. Researchers used physiological signals to activate the capture of multimedia contents based on EDA or ECG variations (Ratsamee et al., 2013; Dobbins and Fairclough, 2017). Again, a phasic or tonic differences on those physiological features may only indicate a change in the ANS not particularly related to individual emotional states. A better approach utilises EEG signals detecting the Event-Related Potential (ERP) to get an insight into the brain responses for emotional perception and it may require a lot more complication in technologies and knowledge (Jiang et al., n.d.).

ERP is an emerging research in neuroscience providing a tool for continuous monitoring for the electrical activities of the brain where a sufficiently large electric field is detectable based on a certain number of nearby simultaneously activated neurons (Bressler and Ding, 2006; Luck, 2014). The P3 component of the ERP has been observed as an association between the CNS and the ANS during the attention of a novel stimulus (Nieuwenhuis, De Geus and Aston-Jones, 2011; Barry, Steiner and De Blasio, 2016; MacDonald and Barry, 2017). Therefore, P3 is viewed as an early indicator for an activity of OR which is the process reflecting the registry of a change in the sensory system ready for a perception and motivation, and also represents that the brain is paying attention to a novel and significant environmental change (Yiend, 2010; Bradley, Keil and Lang, 2012; Yamaguchi and Onoda, 2012).

The experimental results of the current study (see section 6.4) has verified that the OR activities can be used as indicators showing that the emotions are elicited and the perception process has begun. The start of the OR can confirm a window duration for capturing of the corresponding stimuli, or activate the recognition engine for classifier training. Thus, the two questions mentioned at the beginning of this section may have answered. However, the last question for identifying the primal stimulus/stimuli is not ready to be answered yet.

The research for identifying the primal stimulus that stimulate an emotional perception is not obvious. Attention and cognitive science has hypothesised that human attention can be dynamically changed according to situation, a person focusing on watching television can be distracted by a subtle sound from the street asking for help, or a burning smell from the kitchen, or a hallucination activated by a scene from the screen (Wells and Matthews, 2014). However, there is no clue yet on which particular sensory system is getting immediate attention from the detection of the biological change on the human body. More research must be conducted in order to get a clearer picture of the human brain before turning this new knowledge in technology. Clever methods from artificial intelligence may help pick up the sudden changes from the environmental context and associate that with an OR activity.

Response-stimulus synchronisation empowers the investigation of the OR activities using the *emotionWear* framework, and it shows that there is a technology available to identify the human perceptions of novel emotional events through the synchronisation between the stimuli and the responses. This validation of human perception is important for further analysis of emotion recognition in order to enhance the accuracy. However, the reliability of emotional recognition through autonomic specificity is still not high enough for a widespread implementation to the general public. The problem can be profound and complicated. The understanding of human emotions may not be good enough to decipher the actual responses for humans with different culture, personality, experience, age and health. OR is not the only reflex system for attention, there is a defensive reflex which causes a cardiac acceleration instead of the OR's deceleration, especially when humans are having certain types of phobia such as watching disgusting and horror scenes (Graham and Clifton, 1966). The empirical research on OR is mostly focus on audiovisual stimuli, more research should be done on other types of stimuli or even without physical stimuli like those research on acting emotions (Konijn, 2010). The duration for analysing the physiological variables is relatively long, especially those related to HRV which requires a multiple of 24 seconds in order to get a decent amount of data for low frequency features at 0.04Hz (Schäfer and Vagedes, 2013). Research on OR shows an indication on the different deceleration rates for separating pleasant and unpleasant emotions (Codispoti, Surcinelli and Baldaro, 2008), and the using of OR as another fingerprint for emotional ANS specificity can be further exploited.

7.5 Additional results

There are additional results from the *emotionWear* experiment not presented in the published paper (see Chapter 6) due to the limited space allowed for publication purpose. This section describes the missing details for the experiment as follows:

a) Emotional elicitation of selected film clips

Since some participants didn't choose the pre-selected film clips (Chapter 5 section 5.4) for the experiment due to the fact that they were uncomfortable with disgraceful or horrifying scenes, film clip choices were extended to the full list proposed by Schaefer et al. (2010). However, the pre-selected film list was still the basis for the experiment. Table 7.1 illustrates the physiological responses for the 48 tests conducted with the ten participants and the emotional responses for each test including the target, subjective and measured emotion states. Only half of the selected film clips could induce emotions to the participants but their subjective feelings might not be the target emotions of the film clips they watched. OR activities were detected through the algorithm developed in the previous sections, and only around 80% of those detected moments were verified to promote measurable emotional physiological responses.

b) Criteria for participant and stimulus selection

Some participants criticised that the target emotions for certain film clips could not elicit the same emotions to them due to cultural differences. Language barrier might be another obstacle preventing the participant from eliciting similar emotions especially those film contents that required a deep understanding of the dialogue. Therefore, the criteria for psychophysiological research should include the selection of participants with similar culture and language, and the stimulus selection should have considered with the same restrictions.

c) Obsoleted data

There were 11 datasets out of the 48 tests considered as invalid due to motion artefacts and unstable sensor connections. The hand-made sensing glove was proved to be the major reason behind the problem. A better design such as a wristband or sensing watch may solve the mounting problem for attaching sensors to the human body, but the individual sensor structural design and signal processing methodologies could definitely help improve the motion artefacts as well as the unstable mounting.

d) Graphical presentation of all data

All 48 datasets collected from the experiment were preprocessed and feature extracted ready for data analysis. Although some datasets were not useful due mainly to motion

TABLE 7.1: Summary of physiological response results from the *emotionWear* experiment

No.	Selected film clips for experiment (bracketed numbers refer to different clips of the same film)	Target emotions	Subjective emotions	OR detected	Measured emotions
1	Schindlers list [2]	Anger	Sadness	Yes	NA
2	Schindlers list [2]	Anger	Sadness	Yes	Sadness
3	Schindlers list [2]	Anger	NA	No	NA
4	The Dead Peots society [1]	Sadness	NA	Yes	NA
5	American History X	Anger	Sadness	Yes	Sadness
6	Seven [2]	Fear	Disgust	No	NA
7	Les 3 freres	Joy	NA	No	NA
8	ET	Sadness	Sadness	Yes	Sadness
9	Trainspotting [1]	Disgust	Disgust	Yes	Disgust
10	Trainspotting [1]	Disgust	Sadness	No	NA
11	Man bites dog [2]	Anger	NA	No	NA
12	Man bites dog [2]	Anger	NA	No	NA
13	The dinner game	Joy	Joy	No	NA
14	The dreamlife of angels	Sadness	NA	No	NA
15	When Harry met Sally	Joy	Joy	Yes	Joy
16	When Harry met Sally	Joy	NA	No	NA
17	Trainspotting [3]	Disgust	Disgust	Yes	NA
18	Schindlers list [1]	Sadness	NA	No	NA
19	Dead man walking	Sadness	NA	No	NA
20	The Silence of the Lambs	Disgust	Disgust	Yes	Disgust
21	A fish called Wanda	Joy	Joy	Yes	Joy
22	A fish called Wanda	Joy	NA	No	NA
23	A fish called Wanda	Joy	Joy	Yes	Joy
24	The exorcist	Fear	Disgust	Yes	Disgust
25	Sleepers	Anger	NA	No	NA
26	Sleepers	Anger	NA	No	NA
27	Sleepers	Anger	NA	Yes	NA
28	The Shining	Fear	Fear	Yes	Fear
29	The Shining	Fear	NA	No	NA
30	There is something about Mary [2]	Joy	NA	No	NA
31	There is something about Mary [2]	Joy	NA	No	NA
32	Trainspotting [2]	Disgust	NA	No	NA
33	Trainspotting [2]	Disgust	NA	No	NA
34	City of angels	Sadness	NA	No	NA
35	City of angels	Sadness	Sadness	No	NA
36	Misery	Fear	Fear	Yes	Fear
37	Misery	Fear	Fear	Yes	Fear
38	Leave Las Vegas	Anger	NA	No	NA
39	Leave Las Vegas	Anger	NA	No	NA
40	Dangerous minds	Sadness	NA	No	NA
41	Dangerous minds	Sadness	NA	No	NA
42	The Blair Witch Project	Fear	NA	No	NA
43	Hellraiser	Disgust	Fear	No	NA
44	Hellraiser	Disgust	Disgust	No	NA
45	Philadelphia	Sadness	Sadness	No	NA
46	Philadelphia	Sadness	Sadness	No	NA
47	Seven [3]	Disgust	Fear	No	NA
48	Seven [3]	Disgust	Fear	No	NA

artefacts or they could not induce the correct emotions to the participants due to various reasons, they are presented in graphical form for future reference in Appendix D.

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Chapter 8

Conclusions

An artificial sixth sense conceptual framework has been proposed based on a literature review of the current research on electronic engineering, computer science, psychophysiology, cognitive science, neuroscience and biomedical engineering. Missing technologies in emotional response-stimulus synchronisation are identified and hypothesised as a possible cause of delay in turning the concept into a widespread implementation for the general public. A recognition framework based on an idea of response-stimulus synchronisation was built using common contemporary technologies as a proof of concept to verify the hypothesis. The related technologies associated with human cognitive attention for synchronising between stimuli and perception may seem to be falling behind in making an artificial sixth sense system possible for public applications.

The motivation for the current research came from the rise of the IoT, especially the IoS concept evolved from the way of connecting smart sensors across the globe through the Internet. A simple idea of finding a better HCI with ubiquitous computers in the IoT environment developed the research question asking an intuitive way for humans to interact with multiple unnoticeable or invisible computers in the surroundings. Communicating intuitively using contents instead of menu driven approach between machines and humans led the way towards a prediction of human emotional behaviour which was treated by the general public as the sixth sense. A position paper was written and published in an academic journal indicating that an artificial sixth sense system could be built through the IoT after an extensive literature review on IoT technologies and the contemporary methodologies interacting with humans based on intangible interfaces. Further research on Psychology, Psychophysiology and other related disciplines enabled the *emotionWear* framework to be designed and assembled. The *emotionWear* verified the hypothesis that the concept of artificial sixth sense system was not yet ready to be implemented due to the missing technologies for synchronising an emotion perception with the concomitant response. Synchronisation between human attention and emotion established the groundwork for utilising a response-stimulus synchronisation algorithm to validate a true emotion elicitation and to capture the concomitant physiological responses. This response-stimulus technology successfully verified the hypothesis based on the result of an experiment conducted using the *emotionWear* as an emotion recognition platform.

Response-stimulus synchronisation is proven to be a missing technology in real time emotion recognition where an artificial sixth sense system relies on. However, this may not be the only technology that is missing for implementing the emotion recognition for predicting human behaviours. The five basic emotions, although agreed by many researchers studying emotion, are not the only feelings human beings experience. IRS provides an explanation of the differences between individual emotional responses, but variations do occur at different time for the same person. There are subtle tonic and phasic differences between the physiological response in terms of bio-signal variations, and machine learning may be able to get a better statistical prediction through innovative classification rules. However, knowing the true reason behind the pattern of variations for different emotion states is necessary before computational intelligence can be effectively applied. OR supplies valuable hints in synchronising between attention and emotion, but it is limited by novel stimuli and there are other reflex systems such as 'Defensive Response' and 'Startle Response' of the human body that need to be tackled before a complete analysis of a psycho-physiological response is possible. Nevertheless, response-stimulus synchronisation technologies can be used to assist the evaluation of all the problems mentioned above by capturing the correct segments of the responses and stimuli through the hypothesised synchronisation clock.

This chapter further discusses the application of the results, and will lay down the works that can enhance the *emotionWear* for future expansion and widen the areas of application.

8.1 Applications of Results

The idea of synchronisation between emotional responses and the corresponding stimuli is important in a temporal analysis of emotions, there are applications other than the artificial sixth sense that require this synchronisation feature. The accuracy of emotion recognition can be increased since a validation of an emotion elicitation has guaranteed that a true response definitely comes from a perception by the human brain. Subjective feeling may help but empirical evidence has shown that it is not always accurate. On the contrary, the detection of an emotional perception helps initiate the moment to capture the associated stimuli. Similar to the emotional lifelogging application discussed in Chapter 7 section 7.4, there are other operations requiring an emotional event to activate or deactivate so a validation of the emotional perception may fulfil the needs. Analysing the real cause of the particular emotions is another important application, especially for health care assistant. The capturing of the environmental contextual stimuli can be used for feature extraction algorithm to pick up the primal stimulus that causes a specific health issue such as fear conditioning (Maren, Phan and Liberzon, 2013), or anxiety disorder treatment (Wells and Matthews, 2014). The followings show some suggested applications that the design of the *emotionWear* and the result of the current study can apply to enhance their performance or even make them possible:

a) Driver emotion monitoring
   Staying calm behind the wheel can enhance driver alertness and improve road safety. Monitoring driver's emotions during driving has been promoted and wearable sensing or remote imaging techniques are being used to assist driving attitude. Emotion prediction can help remind drivers for possible emotional fluctuation before driving on the road through monitoring driver current emotion state as well as the predicted emotion state for coming environment of the road ahead. Artificial sixth sense server stores past emotional response history for each driver and can be used for statistical prediction for future or remote stimuli.

b) Learning in classroom analysis
   Increasing situational interest in the classroom can improve student engagement in learning. Monitoring students' emotional behaviours through the response-stimulus synchronisation enables an immediate feedback for adjusting the training materials.

Wearable sensors can be worn by each student for collecting their real time physiological responses, and a gateway inside the classroom will receive physiological data from individual sensor through a wireless channel.

c) Music recommendation system
Song recommendation has been an emerging topic for the music industry. Response-stimulus synchronisation can help collect listeners' responses based not only on the type of songs through the genre classification for a specific song, but also the rhythm for a particular section of the song captured by the synchronisation algorithm. Songs with matching rhythm can then be recommended to the users. Sensors can be embedded into the earphone with an extension to the earlobe which provides a good bio-signal collection for heart rate through a earlobe PPG sensor (Vescio et al., 2018), and skin temperature can be extracted through thermal sensor measuring the tympanic membrane at the end of the ear canal (Propper and Brunyé, 2013). More research should be done on all emotional physiological signals on or around the human ears which are less subject to motion artefacts during ambulatory measurement than other body peripherals.

d) Mental therapy for depression or anxiety
Knowing the cause of depression or anxiety can be helpful for mental therapy. Response-stimulus synchronisation helps find out the stimuli that induce the target emotions, especially for those patients without the ability or unwilling to express their feelings (e.g. people with autism or dementia). Wearable sensing or remote sensing would help monitor the patients' physiological responses, and together with the recording of the environmental contexts are critical in analysing the cause of the symptom. Synchronisation may be able to identify the types of stimuli for further analysis and make the right diagnosis.

8.2 Future Works

The practical implementation of the artificial sixth sense system through the IoT is definitely a goal according to the current research, however, the technologies for emotional response-stimulus synchronisation must be mature enough for the implementation to succeed. There are several areas related to the response-stimulus synchronisation that may need more rigorous research. Firstly, the physiological changes concomitant to an emotional perception can be observed by the OR activities (Bradley, 2009) or the similar detection of the P3 component of ERP (Barry, Steiner and De Blasio, 2016), they are treated as close association with each other (Nieuwenhuis, De Geus and Aston-Jones, 2011; Bradley, Keil and Lang, 2012) and a detailed empirical study may reveal some differences under various stimulations, but research on this area is not obvious. Moreover, OR activities on audiovisual stimuli are extensively researched but other types of stimuli such as haptic, olfactory and gustatory are having relatively less attention. Secondly, the empirical study on the rate of cardiac deceleration on different emotions under different stimuli for emotion specificity is not actively researched. There are indications from previous research showing observable differences in the rate of deceleration for pleasant and unpleasant emotions (Codispoti, Surcinelli and Baldaro, 2008). Similarly, the defensive response causing cardiac acceleration instead of the normal OR should also be studied to fill in the gap since a defensive response also occurs for cognitive attention to extremely unpleasant stimuli. Finally, the identification of the primal stimulus from a collected conditioned and unconditioned stimuli can help get a clear picture of response-stimulus relationship for health care and clinical applications.

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Appendices

Appendix A

Off-The-Shelf Biomedical Sensors

Only common biomedical sensors that can be purchased from online resources are used in the present research, and their details are listed below.

- PPG (Photoplethysmography)
  Pulse Sensor is an open source hardware project by Joel Murphy and Yury Gitman, and the specification can be obtained from `https://pulsesensor.com/pages/open-hardware`.
- EDA (Electrodermal Activity)
  Grove GSR Sensor from Seeed; specification can be obtained from `http://wiki.seeed.cc/Grove-GSR_Sensor/`.
- SKT (Skin Temperature)
  Si7051 Digital Temperature Sensors with I2C Interface from Silicon Labs; specification can be obtained from `https://www.silabs.com/products/sensors/si705x-temperature-sensors`.
- EMG (Surface Electromyography)
  MyoWare Muscle Sensor from Advencer Technologies; specification can be obtained from `http://www.advancertechnologies.com/p/myoware.html`.
- Glove
  A Bracoo TP30 Thumb & Wrist Brace for holding the PPG, EDA sensors from `https://www.amazon.co.uk/gp/product/B00JQM9126/ref=ppx_yo_dt_b_asin_title_o08_s00?ie=UTF8&psc=1`.

Appendix B

Application for Ethical Clearance from the Ethics Committee of the University of Reading

The protocol for the emotion recognition experiment using the *emotionWear* framework was subject to ethical clearance and the application and approval details are listed in this appendix.

Submission date: 29th September 2017

Approval date: 28th November 2017

SBS17-18 10

School of Biological Sciences
Ethics Committee - Project Approval

Principal Investigator(s) Professor Simon Sherratt
Other researchers involved Terence Kam Luen Hui (PhD student)

School/course/other Biological Sciences

Title of project
Towards Disappearing User Interface in Ubiquitous Computing: Human Enhancement from Sixth Sense to Super Senses

Submitted 29 September 2017

Referred to Head of School 28 November 2017

Stage 1 Revision asked for 11 October 2017

Stage 2 Revised version received 19 October 2017

Stage 3 Comments received and passed on from member of SBS Local Ethics Committee

Stage 4 Re-revised version received and approved 28 November 2017

Chair of Ethics Committee: Dr David S. Leake (acting chair)

[redacted]

Date: 28 November 2017

Head of School: Prof. Rob Jackson

Date:

[redacted]

Biomedical Engineering

University of Reading

Ethical Clearance Application

Research Project:
Towards Disappearing User Interface in Ubiquitous Computing: Human Enhancement from Sixth Sense to Super Senses

Date: 27th November 2017

Principle Investigator: R. Simon Sherratt

TABLE OF CONTENTS

INFORMATION FOR THE ETHICS COMMITTEE

1. Summary

Title: Towards disappearing user interfaces for ubiquitous computing: human enhancement from sixth sense to super senses.

Human emotion is a critical part of user interactions with ubiquitous computing realised as the Internet of Things (IoT). The recognition of emotional responses becomes necessary in the IoT when tailor made services are needed to be provided to selected users according to their intentions. What types of sensors for collecting specific human emotions is a question waiting to be answered. Our current project focuses on getting a deeper knowledge of the relationship between biomedical sensors and the corresponding measurable human emotions. We target on wearable sensors at the beginning to limit the scope for a reasonable research time frame.

2. Selection and recruitment of participants

We will recruit human subjects for conducting experiments by showing emotional films as stimuli and collect their corresponding physiological responses using common commercial wearable sensors. Only 4 different types of sensors are chosen to do the measurements: PPG (Photoplethysmography), EMG (Electromyography), EDA (Electrodermal Activity), and SKT (Digital Temperature Sensor on skin surface).

2.1 Selection criteria for participants

Criteria for selecting participants are adults (age 18+) without any diagnosed medical conditions (e.g. diabetes, heart disease, sweating disorders such as hyperhidrosis or hypohidrosis). Each participant will be presented with several types of emotional stimuli and their corresponding physiological responses are recorded using non-invasive biomedical wearable sensors thus a healthy individual is required. Age and sex differences do exist but is minimum in emotional physiological responses based on the particular sensors we have chosen.

2.2 Recruitment process

Around ten (10) participants will be recruited for the study, and each will be presented with several types of emotional stimuli and their corresponding physiological responses are recorded using non-invasive biomedical wearable sensors. The whole experiment will be completed in one (1) hours.

An email will be sent to all university's students to recruit participants with email content as below:

Greetings.

My name is <<Name>> and I am a PhD student working with Biomedical Engineering at the University of Reading. We are conducting a research study about emotion recognition using non-invasive wearable biomedical sensors. I am looking for participants aged 18+ without any diagnosed medical conditions (e.g. diabetes, heart disease, sweating disorders such as hyperhidrosis or hypohidrosis). Participation is completely voluntary and your data will be anonymous.

Participation in this study involves:

- An experiment session of around 1 hour in a laboratory watching emotional media (pictures, audio, or films) and wearing non-invasive sensors for measuring the corresponding responses.
- At the end of the session, completing a questionnaire summarizing your emotions while you were watching/listening to the media.
- Participant will be offered a £5 Sainsbury's Voucher at the completion of the experiment.

If you are interested, please email <<email>> to arrange a time slot to conduct the study.

If you have any questions, please do not hesitate to contact me <<email>>.

Thank you.

3. Procedures of project

A brief procedure for the experiment of this project is listed below:

3.1 Subject registration: each subject will be briefed on the project and experiment by the investigator explaining the details listed on the "Information Sheet for Participants".

3.2 Investigator will fill in the questionnaire and collect basic details of participants (such as age range, and sex, etc.) according to the "Questionnaire" form. Investigator also explains the potential risks of emotional harm for watching irritating materials especially those eliciting fear, disgust and anger emotions. Participants can refuse to watch those materials if they feel uncomfortable, thus the investigator will only select and show to the participants the appropriate visual stimuli. Investigator will help choose one film clip from each emotion category for the study and the IAPS slideshow under the participant's agreement.

3.3 The maximum duration for the film clips is less than 6 mins (section 4.1) and the slideshow is 9 mins, plus the handling time between switching media, the total study period is less than 1 hour.

3.4 Subject will wear a VR headset (or google cardboard) where an android phone is installed inside for showing the emotional films and collect data from the wearable sensors through Bluetooth wireless connection. The subject may need to adjust the focus on the VR headset in order to get a clear picture according to the instruction from the investigator.

3.5 The investigator will help the subject to wear a glove with wearable sensors installed and the sensors are wirelessly connected and controlled by the android phone in the VR headset.

3.6 The investigator will need to make sure all wearable sensors are properly installed and the biomedical signals picked up are at the highest quality.

3.7 Experiment will start and the film watching and data collection are performed automatically.

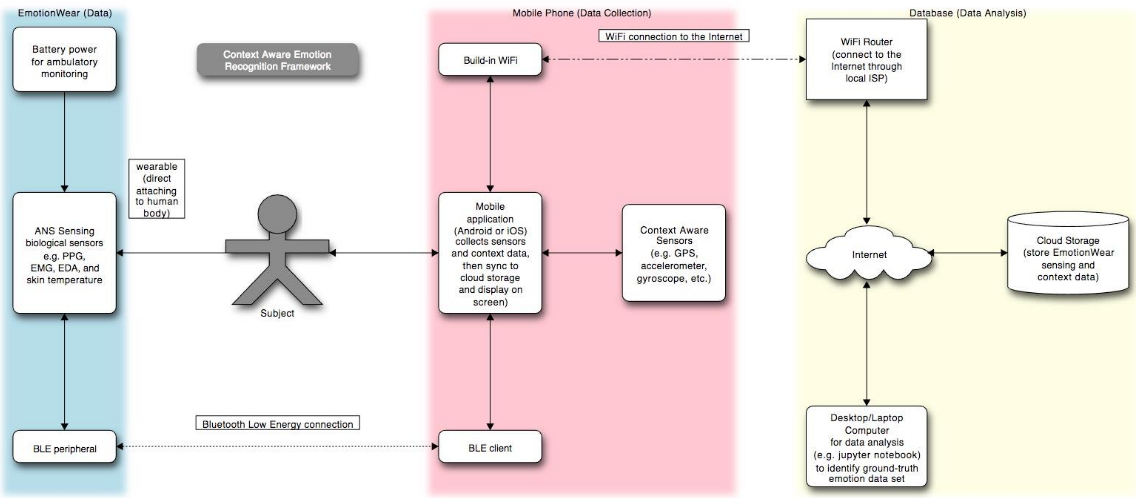
3.8 When the experiment stops, investigator will help the subject to remove the sensors and the VR headset.
3.9 Investigator will continue filling the unfinished questionnaire and collect subjective feelings from the subject.
3.10 Experiment ends and the subject can collect the "Information Sheet for Participants" which shows the contact information if required for future communication.

The following equipment and tools are required before the experiment is started:

i) VR headset: for holding an Android phone which will play the emotional films as stimulus to the subject and the wireless collection of biomedical sensor signals from the wearable sensors.
ii) Wearable sensor glove: for mounting the sensors measuring in real time the corresponding biomedical signals which are synchronised with the visual stimulus.
iii) The documents "Information Sheet for Participants" and "Questionnaire" are presented in hard copies as written records for participants and investigator respectively.

4. Data collection and analysis

Anonymous data is uploaded to a cloud storage with password protected. A data analysis program written in Python will be used to analyse the emotional responses of every subject according to the film they have watched, specific time patterns of the combined biomedical signals will be marked to show the accuracy of emotion recognition. Below is the block diagram of the data collection and analysis of this project.



4.1 Stimulation of emotions

Human emotions promote both physiological and behavioural responses under a sensation to stimulation to perception process, and the common stimuli are audio or visual. A set of emotional stimuli designed by University of Florida, the IAPS (International Affective Picture System), has been heavily researched and used by many researchers as references in stimulating human emotions [1, 2]. IAPS supplies 1128 still pictures without auditory content and we have selected 20 from the database. Half of the 20 selections are having the highest valence rating and the rest are the 10 lowest-rated pictures according to their report attached to the database package. Film clips using in this study were rated and classified by Schaefer et al. [3] and some films were also investigated by Gross & Levenson [4]. All film clips come from commercial movies and can be downloaded from related web sites mentioned in the articles. The current study adopts both still pictures stimuli compiled as slideshow with no auditory content and film clips as audiovisual stimuli to elicit different emotional states for taking physiological measurements. Both slideshow and film clips are pre-processed and complied into mpeg layer 4 or mp4 format for easy handling on our experimental framework.

The following table summarise the stimuli and the expected emotion elicitation:

Emotions	IAPS [2]	Film clips [3]
Happiness	High valence rating: #1710 (Puppies), #1750 (Bunnies), #5833 (Beach), #1460 (Kitten), #2050 (Baby), #1440 (Seal), #2040 (Baby), #2070 (Baby), #8190 (Skier), #2080 (Babies) Low valence rating: #3053 (BurnVictim), #3102 (BurnVictim), #3000 (Mutilation), #3064 (Mutilation), #3170 (BabyTumor), #3080 (Mutilation), #3063 (Mutilation), #9410 (Soldier), #3131 (Mutilation), #3015 (Accident) Each picture is displayed for 6 seconds and followed by 20 seconds blank (black) screen, so a total of 520 seconds or 8 minutes 40 seconds to complete this slideshow.	1. There is something about Mary [Mary (Cameron Diaz) takes sperm from Ted's hair (Ben Stiller) mistaking it for hair gel.] – 2:25 2. A fish called Wanda [One of the characters (John Cleese) is found naked by the owners of the house.] – 3:01 3. When Harry met Sally [Sally simulates an orgasm in a restaurant.] – 2:52
Anger		1. Schindler's list [A concentration camp commander randomly shoots prisoners from his balcony.] – 2:00 2. Sleepers [Sexual abuse of children.] – 2:24 3. Leaving Las Vegas [The main character is raped and beaten by three drunk men.] – 2:35
Fear		1. The Blair Witch Project [Final scene in which the characters are apparently killed.] – 4:00 2. The Shining [The character played by Jack Nicholson pursues his wife with an axe.] – 4:26 3. Misery [Annie (Kathy Bates) breaks Paul's legs (James Caan).] – 3:40
Disgust		1. Trainspotting [The main character dives into a filthy toilet.] – 1:49 2. Seven [Policemen find the body of a man tied to a table.] – 3:27 3. Hellraiser [On the floor, the size of two stains are growing, and progressively transforming into a monster with a human-like skeleton.] – 1:30
Sadness		1. City of angels [Maggie (Meg Ryan) dies in Seth's (Nicolas Cage) arms.] – 4:25 2. Dangerous mind [Students in a school class are told that one of their classmates has died.] – 2:12 3. Philadelphia [Andrew (Tom Hanks) and Joe (Denzel Washington) listen to an opera aria on the stereo. Ted describes to Joe the pain and passion felt by the opera character.] – 5:28

4.2 Measurement of emotions

Measurement of physiological responses promoted by emotions can be done using biomedical sensors and we are using four common types of bio-sensors: PPG to measure the heart beats and heart rate variability, EDA to measure the skin conductance, EMG to measure the muscle contraction, and digital temperature sensor to measure skin temperature Tsk. Emotion activates the Autonomic Nervous System (ANS) and influences different visceral organs to promote physiological responses which reflect certain patterns of biosignals. These patterns become ANS specificity which is the foundation for emotion recognition using physiological measurements [5]. Emotion recognition can then be derived from the patterns of biosignals.

4.3 Subjective feeling

This is a good practice for conducting emotion recognition research using direct measurement to add a subjective feeling from the subject in order to qualify the collected data. Since we have arranged different IAPS's materials into various time slot in a video, the responses from the participants should match with the associated stimuli. Therefore, a subjective feeling from the participants can be used to verify whether the elicited emotions are the expected ones. The collected biomedical data, together with the subjective feedback will be used for analysis after the experiments.

4.4 Value of the study

Emotion recognition has been researched for decades and ANS specificity has been treated as empirical evidence for accurate physiological measurement on human emotions. The current study aims to apply human emotion recognition using wearable sensors into IoT environment to further improve the intelligence of Smart homes in Smart Cities by getting affective feedback from users in ubiquitous computing[6] [7].

5. References

1. Lang, P.J., M.M. Bradley, and B.N. Cuthbert, *Emotion, attention, and the startle reflex*. Psychological review, 1990. **97**(3): p. 377-395.
2. Lang, P.J., M.M. Bradley, and B.N. Cuthbert, *International affective picture system (IAPS): Affective ratings of pictures and instruction manual*, in *Technical report A-8*. 2008, University of Florida: Gainesville, FL.
3. Schaefer, A., et al., *Assessing the effectiveness of a large database of emotion-eliciting films: A new tool for emotion researchers*. Cognition and Emotion, 2010. **24**(7): p. 1153-1172.
4. Gross, J.J. and R.W. Levenson, *Emotion elicitation using films*. Cognition & emotion, 1995. **9**(1): p. 87-108.
5. Levenson, R.W., *The Autonomic Nervous System and Emotion*. Emotion Review, 2014. **6**(2): p. 100-112.
6. Hui, T.K.L., R.S. Sherratt, and D.D. Sánchez, *Major requirements for building Smart Homes in Smart Cities based on Internet of Things technologies*. Future Generation Computer Systems, 2017. **76**(Supplement C): p. 358-369.
7. Hui, T.K.L. and R.S. Sherratt, *Towards disappearing user interfaces for ubiquitous computing: human enhancement from sixth sense to super senses*. Journal of Ambient Intelligence and Humanized Computing, 2017. **8**(3): p. 449-465.

PROJECT SUBMISSION FORM

<u>Note</u> All sections of this form should be completed.
Please continue on separate sheets if necessary.

Principal Investigator: Professor R. Simon Sherratt

School: Biological Sciences (Department of Biomedical Engineering)

Email: [redacted]

Title of Project: Towards disappearing user interfaces for ubiquitous computing: human enhancement from sixth sense to super senses

Proposed starting date: Dec 2017

Brief description of Project:

Using common commercial biomedical wearable sensors to measure non-invasively human heart rate, skin conductance, muscle contraction, and skin temperature for emotion recognition.

I confirm that to the best of my knowledge I have made known all information relevant to the School Research Ethics Committee and I undertake to inform the Committee of any such information which subsequently becomes available whether before or after the teaching/research has begun.

I confirm that if this project is an interventional study, a list of names and contact details of the subjects in this project will be compiled and that this, together with a copy of the Consent Form, will be retained within the School for a minimum of five years after the date that the project is completed.

Signed:

[redacted].. Date: …28th Nov 2017…………

(Investigator)

……………………………………………………... Date: ……………………………………

(Head of School or authorised Head of Department)

[redacted]Date: ……27th Nov 2017……….

(Student) Terence K.L. Hui

Checklist

1. This form will be submitted to the School Research Ethics Committee and will subsequently, if approved, be signed by my Head of School (or authorised Head of Department) ☑

2. The Consent form includes a statement to the effect that the application has been reviewed by the School Research Ethics Committee and has been given a favourable ethical opinion for conduct ☑

3. I have made, and explained within this application, arrangements for any confidential material generated by the teaching/research to be stored securely within the University and, where appropriate, subsequently disposed of securely. ☑

4. I have made arrangements for expenses to be paid to participants in the research, if any, OR, if not, I have explained why not. ☑

5. EITHER

   (a) The proposed teaching/research does not involve the taking of blood
   samples; ☑

   OR

   (b) For anyone whose proximity to the blood samples brings a risk of Hepatitis B, documentary evidence of immunity prior to the risk of exposure will be retained by the Head of School or authorized Head of Department. ☐

   Signed:

   ………………………………………………………Date……………………………………

   (Head of School or authorised Head of Department)

6. EITHER

   (a) The proposed teaching/research does not involve the storage of human tissue, as defined by the Human Tissue Act 2004; ☑

   OR

   (b) I have explained within the application how the requirements of the Human Tissue Act 2004 will be met. ☐

7. EITHER

(a) The proposed teaching/research will not generate any information about the health of participants; ☑

OR

(b) If the teaching/research could reveal adverse information regarding
the health of participants, their consent to pass information on to their GP will be included in the consent form and in this circumstance I will inform the participant and their GP providing a copy of the relevant details to each and identifying by date of birth; ☐

OR

(c) I have explained within the application why (b) above is not appropriate. ☐

8. EITHER

(a) the proposed research does not involve children under the age of 5; ☑

OR

(b) My Head of School (or authorised Head of Department) has given details of the proposed research to the University's insurance officer, and the research will not proceed until I have confirmation that insurance cover is in place. ☐

Signed:

………………………………………………………Date……………………………………

(Head of School or authorised Head of Department)

This form and further relevant information (consent form and information sheet) should be returned electronically to:

Dr. M. Alejandra Perotti
Email: m.a.perotti@reading.ac.uk

You will be notified of the Committee's decision as quickly as possible, and you should not proceed with the project until a favourable ethical opinion has been passed.

Biomedical Engineering

University of Reading

INFORMATION SHEET FOR PARTICIPANTS

1. Research project title

Towards disappearing user interfaces for ubiquitous computing: human enhancement from sixth sense to super senses.

2. Purpose of the project

This research project aims to investigate how wearable biomedical sensors can recognise human emotions through measureable physiological responses. The promotion of emotions relies on emotional film watching, and the measurement of biosignals is done non-invasively via four common commercial available biomedical sensors (i.e. PPG [photoplethysmography] for heart rate, EMG [electromyography] for muscle contraction, EDA [electrodermal activity] for skin conductance, and digital temperature sensor for skin temperature). This project builds on the concept that each individual sensor can be part of the IoT (Internet of Things) network which extends the human sensory system once each individual is network connected.

3. Participation

What does participation in this study involve?

- An experiment session of around 1 hour in a laboratory watching and listening to emotional media (pictures, audio, or films) and wearing non-invasive sensors for measuring the corresponding responses.
- At the end of the session, completing a questionnaire summarizing your emotions while you were watching/listening to the media.
- Participant will be offered a £5 Sainsbury's Voucher at the completion of the experiment.

Where will the studies take place?

- All studies will take place during office hours in the department of Biomedical Engineering.

Who would we like to participate in this study?

- Adults (age 18+) without any diagnosed medical conditions (e.g. diabetes, heart disease, sweating disorders such as hyperhidrosis or hypohidrosis).

Will I be paid for my participation?

- Each participant will be offered a £5 Sainsbury's Voucher for the participation of the study.

What are the risks for my participation?

- There are no risks involved in taking part. There will be irritating scenes or pictures for eliciting various emotions such as fear, anger or disgust, and you can choose not to watch those scenes if you don't feel comfortable.

Can I change my mind at any stage and withdraw from the study?

- Absolutely, you are free to withdraw from the study at any time without giving reason, and this will be without detriment.

4. Confidentiality

All the information that we collect about you during the course of the research will be kept strictly confidential. Names will not be attached to any data nor questionnaires, which will be identified only by an anonymous code number. Any data collected about you will be stored electronically in a University of Reading network drive protected by passwords and other relevant security processes and technologies with access restricted to the research group.

Data collected may be shared in an anonymised form to allow reuse by the research group and other third parties for analysis and may be published anonymously in a research paper. These anonymised data will not allow any individuals or their institutions to be identified or identifiable.

5. Contacts for further information

Investigator: Terence Hui, PhD student, Department of Biomedical Engineering, School of Biological Sciences, The University of Reading, RG6 6AY, UK, email: [redacted]

Project supervisor: Prof. R. Simon Sherratt, Professor of Biosensors, Department of Biomedical Engineering, School of Biological Sciences, The University of Reading, RG6 6AY, UK, Tel: [redacted], email: [redacted]

6. Ethical review procedure

This project has been subject to ethical review, according to the procedures specified by the University Research Ethics Committee and has been given a favourable ethical opinion for conduct.

Please feel free to contact us if you would like any more information on this study.

Thank you for your help.

Biomedical Engineering

University of Reading

CONSENT FORM

1. I have read and had explained to me by .... the accompanying Information Sheet for Participants relating to the project on "Towards disappearing user interfaces for ubiquitous computing: human enhancement from sixth sense to super senses".

2. I have had explained to me the purposes of the project and what will be required of me, and any questions I have had have been answered to my satisfaction. I agree to the arrangements described in the Information Sheet in so far as they relate to my participation.

3. I understand that participation is entirely voluntary and that I have the right to withdraw from the project at any time, and that this will be without detriment.

4. This project has been subject to ethical review, according to the procedures specified by the University Research Ethics Committee and has been given a favourable ethical opinion for conduct.

5. I have received a copy of this Consent Form and of the accompanying Information Sheet for Participants.

Name: ________________________________

Signed: ________________________________

Date: ________________________________

QUESTIONNAIRE

This questionnaire is filled up by the project coordinator before and after the experiment of the research project. (CODE: ______________________)

1. AGE (must be over 18)	☐ >18 ≤30 ☐ >30 ≤50 ☐ >50 ≤70 ☐ >70
2. Sex	☐ male ☐ female ☐ prefer not to say
3. Type of stimulus	☐ IAPS pictures, or ☐ film/ filename: ______________________
4. Types of measurement	☐ PPG ☐ EMG ☐ EDA ☐ SKT
5. Date (yyyy-MMM-dd, HH:mm:ss)	Start: ______________________ End: ______________________
6. Subjective feeling	☐ happiness/ at: ______________________ ☐ sadness/ at: ______________________ ☐ anger/ at: ______________________ ☐ disgust/ at: ______________________ ☐ fear/ at: ______________________ ☐ others/ at: ______________________ ______________________ ______________________ ______________________ ______________________

CONTINUE ON NEXT PAGE

Comments:

END OF QUESTIONNAIRE

Appendix C

Responses to comments for Ethical Clearance

Two revisions of the research protocol were submitted to the Ethics Committee for getting approval from the Ethical Clearance process for the current research, this "responses to comments" document was included in the third round of submission.

Submission date: 29th September 2017

Approval date: 28th November 2017

Responses to reviewer's comments dated 15/11/2016

Document:	Ethical Clearance Application (13/10/2017)
Title:	Towards Disappearing User Interfaces for Ubiquitous Computing: Human Enhancement from Sixth Sense to Supersenses
Researcher:	Terence KL Hui (student #: 22847177)
Supervisor:	Professor R. Simon Sherratt
Date:	27^{th} November 2017

Email comments:

****

COMMENT #1- We would like to have further clarification on the content of the films. Is there any possibility that the content will be upsetting/distressing to participants and if so, what is the rationale for that and how will participants be supported if they do become distressed?

RESPONSE #1- We have listed out in section 4.1 all pictures (with reference numbers from IAPS database) and film clips using in this study with the duration of each media file. The 20 chosen IAPS pictures are compiled into a slideshow in mp4 format, which is the same format as the film clips, for easy handling in our framework. Each IAPS picture and film clip is proven from previous studies (see section 4.1) for emotion elicitation during empirical research on emotions. The investigator will ask the participant at the beginning (section 3.2) whether they will feel uncomfortable for certain kind of emotions by watching associated scenes, especially for those related to fear, anger, and disgust. Participants will be informed about the potential risks of emotional harm and they can choose not to watch those type of media. Investigator will then choose one film clip from each emotion category together with the IAPS slideshow for the study under the agreement of the participant. The maximum duration for the film clips is less than 6 mins and the slideshow is 9 mins, plus the handling time between switching media, the total study period is less than 1 hour (section 3.3). Section 3 in the "Information Sheet for Participants" also reminds the participant this potential risk of emotional discomfort.

COMMENT #2- We would like to have further clarification on the participant experience, particularly (a) it says "Selection of emotional films is done by the subject with the help from the investigator." – do the participants need to follow certain criteria in selecting the films and if so what are the instructions to the participants? (b) How many films will each participant watch, how long is each film, any rest breaks?

RESPONSE #2- The original Android application was designed to be flexible for selecting media file by the participant wearing the VR headset. We have changed this operation to simplify the selection and limited the control to the investigator according to the agreement made at the beginning of the study with the participant (section 3.2). The total study time per participant will not be more than 1 hour.

COMMENT #3- Section 4 of the questionnaire lists what measurements will be taken, and there is an option for “other”. But the info sheet and application don’t mention "other". EITHER confirm that there is no "other" OR modify the info sheet and application to explain what this "other" might be.

RESPONSE #3- We have removed the “other” option and kept only 4 types of physiological measurements.

Document (PDF) comment:

****

COMMENT #1- page 3: example email for recruiting participants

RESPONSE #1- 1) 3 typos are corrected, 2) participant involvement listed in the email is the same as information sheet, 3) participant’s involvement listed in the email also is alos stated in the information sheet for participants, 4) send email to <<email>> is added.

COMMENT #2- page 3: Procedures of project section 3.5 and 3.6

RESPONSE #2- 1) 3.5: remove the sentence “Selection of emotional films is done by the subject with the help from the investigator.”, since we have changed the Android app so no selection is required during the operation and selection of media file is done by the investigator only, 2) 3.6: change filming to film, there is no filming during the experiment.

COMMENT #3- page 4: section 4.1 Stimulation of emotions

RESPONSE #3- Clarify in details of the selections of IAPS pictures and the film clips, a table is added to list out each file. We have added the description on how IAPS pcitures are compiled into slideshow in mo4 format.

COMMENT #4- page 9 Information Sheet for Participant, section 3

RESPONSE #4- 1) added a section on Where will the studies take place, 2) correct type and grammatical mistakes.

COMMENT #5- page 10 Information Sheet for Participant, section 4

RESPONSE #5- remove "Data will be stored in electronic format for up to 5 years.

COMMENT #6- page 12 Questionnaire

RESPONSE #6- 1) row 3, changed the selection of multiple files to only select one file, either IAPS slideshow or film clip with file name. So one questionnaire is reserved for one media file as stimulus and record the corresponding physiological measurements. 2) removed other in row 4 to limit the study on four specified biosensors only.

Appendix D

Physiological response data collection

The 48 datasets of physiological responses from the *emotionWear* experiment are attached as graphical presentation in this appendix for references. Each participant is assigned a non-traceable number with some generic data attached to each record, and the description for utilisation of this data can be found from Chapter 6 and Chapter 7. The red vertical lines are the OR moments validated by an ER-SC plus a HR deceleration, and the label for each graph refers to table 7.1.

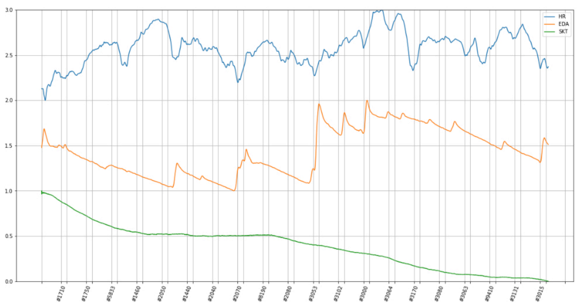
Participant number: EP1

Age: $>50 \leq 70$

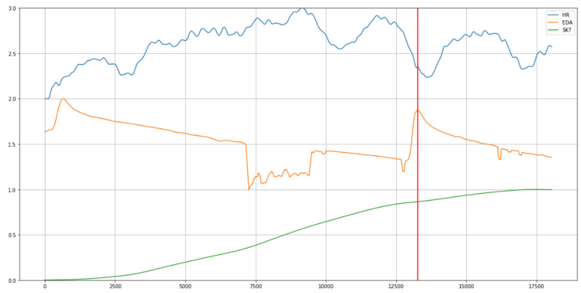
Sex: Male

Stimuli selected:

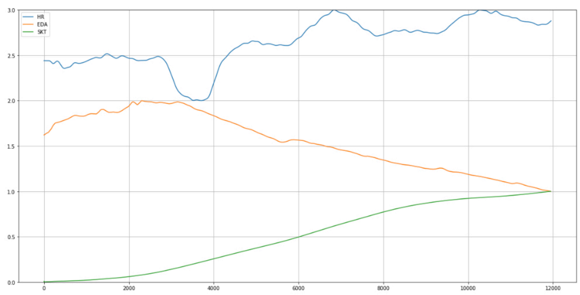
- Still pictures = IAPS film clip (iaps 01)
- Joy/Happiness = A fish called Wanda (test 21)
- Anger = Schindlers list [2] (test 03)
- Fear = Misery (test 36)
- Disgust = The Silence of the Lambs(test 20)
- Sadness = City of angels (test 34)



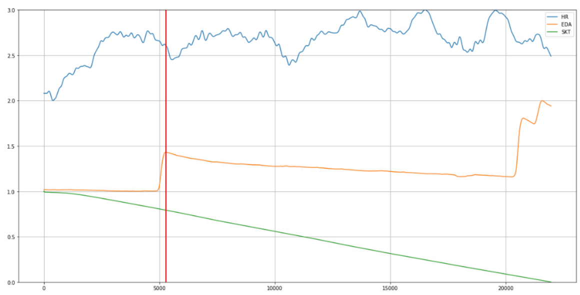
IAPS response (iaps 01)



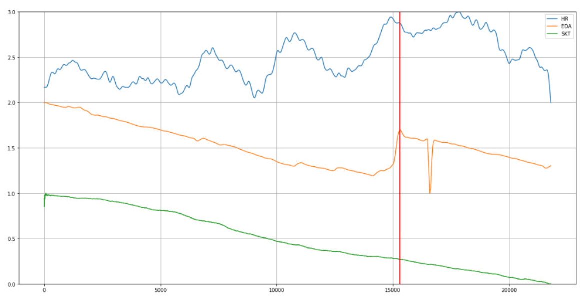
Test 21 (OR detected, Joy)



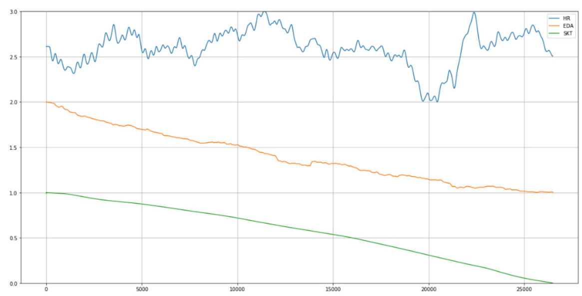
Test 03 (no OR detected)



Test 36 (OR detected, Fear/Anger)



Test 20 (OR detected, Disgust)



Test 34 (no OR detection)

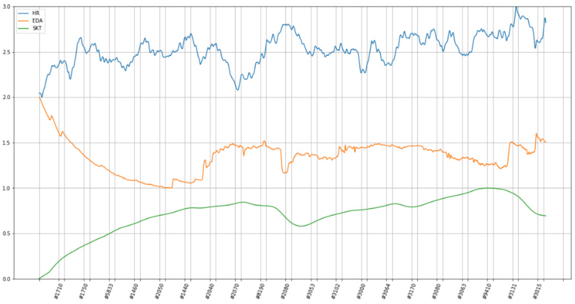
Participant number: EP2

Age: $>50 \leq 70$

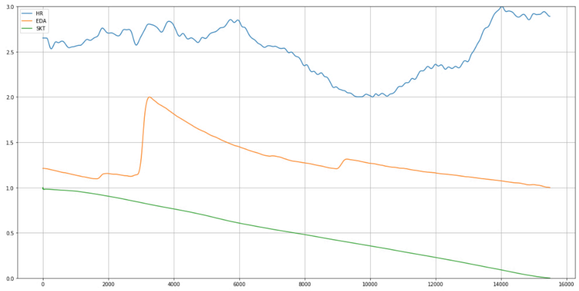
Sex: Male

Stimuli selected:

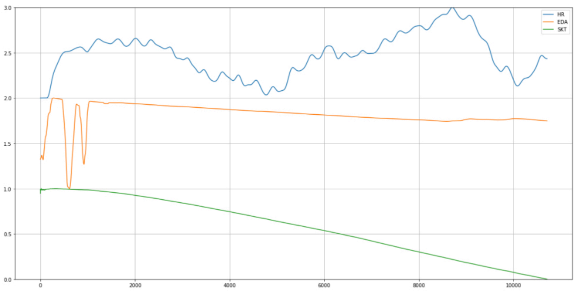
- Still pictures = IAPS film clip (iaps 02)
- Joy/Happiness = selected two film clips from Disgust category
- Anger = Leave Las Vegas (test 38)
- Fear = Seven [2] (test 06)
- Disgust = Trainspotting [1] (test 09)
- Disgust = Seven [3] (test 47)
- Sadness = ET (test 08)



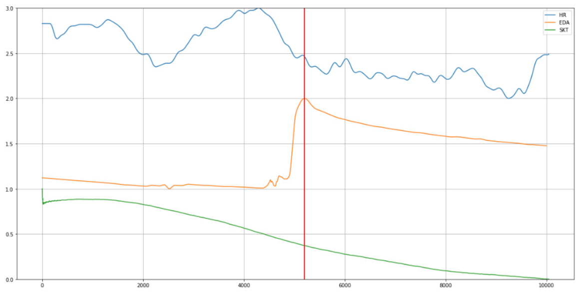
IAPS response (iaps 02)



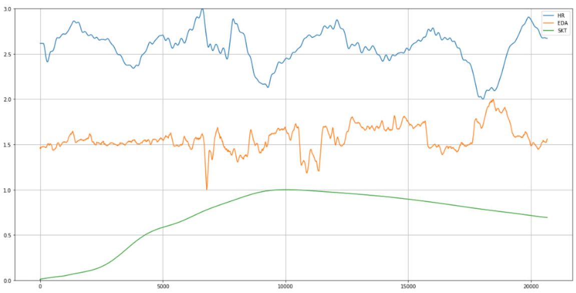
Test 38 (no OR detected)



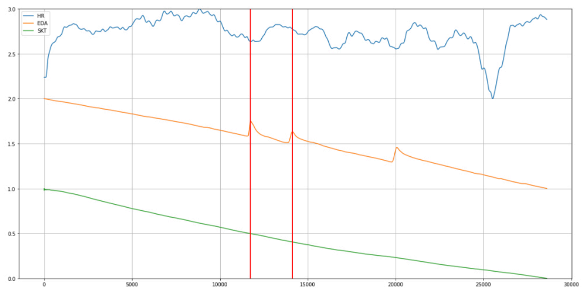
Test 06 (unstable connection)



Test 09 (OR detected, Disgust)



Test 47 (motion artefacts)



Test 08 (2 OR detected, Sadness + Sadness)

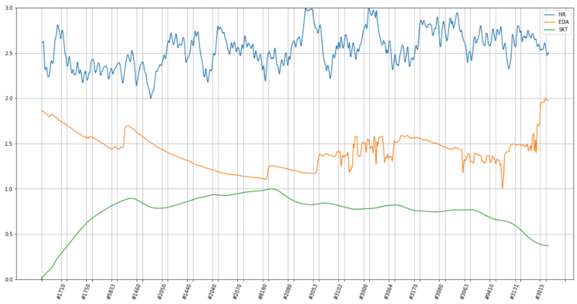
Participant number: EP3

Age: $>30 \leq 50$

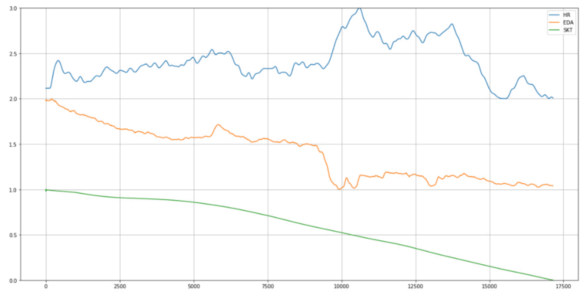
Sex: Male

Stimuli selected:

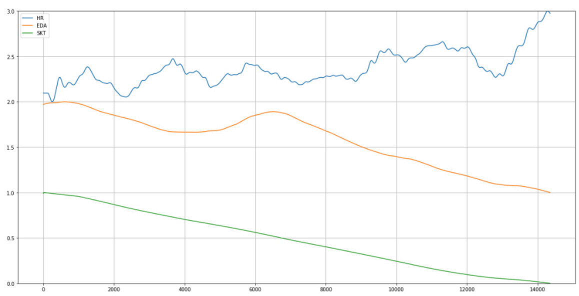
- Still pictures = IAPS film clip (iaps 03)
- Joy/Happiness = When Harry met Sally (test 16)
- Anger = Sleepers (test 26)
- Fear = The Shinning (test 28)
- Disgust = Trainspotting(test 32)
- Sadness = City of angels (test 35)



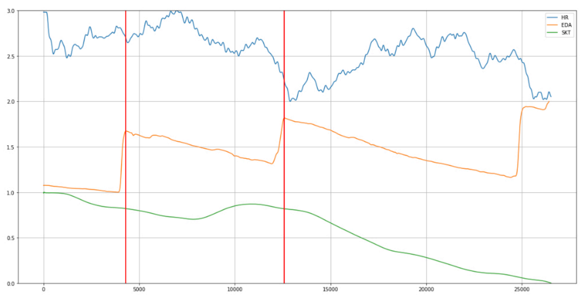
IAPS response (iaps 03)



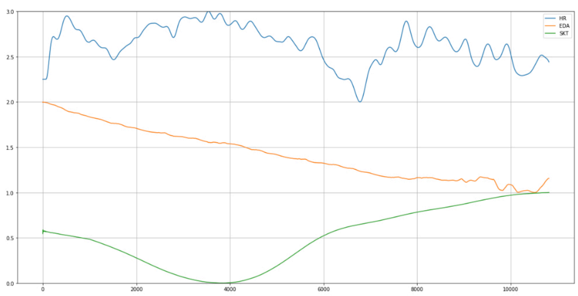
Test 16 (no OR detected)



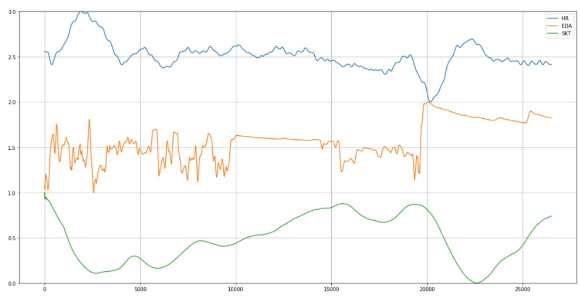
Test 26 (no OR detected)



Test 28 (2 OR detected, Disgust + Fear/Anger)



Test 32 (no OR detected)



Test 35 (motion artefacts)

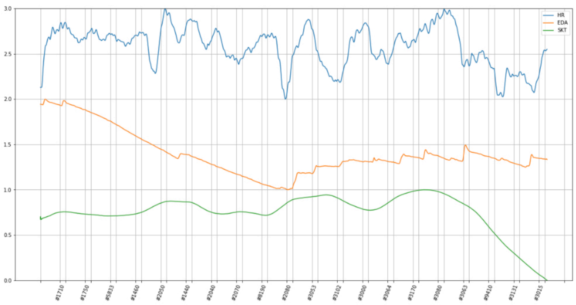
Participant number: EP4

Age: $>30 \leq 50$

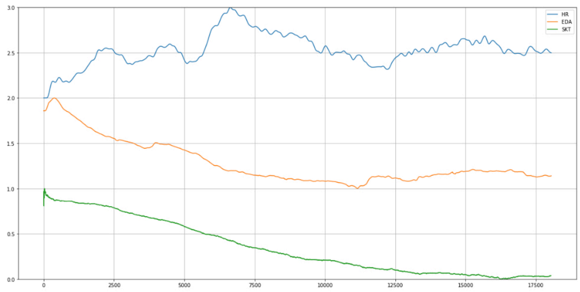
Sex: Male

Stimuli selected:

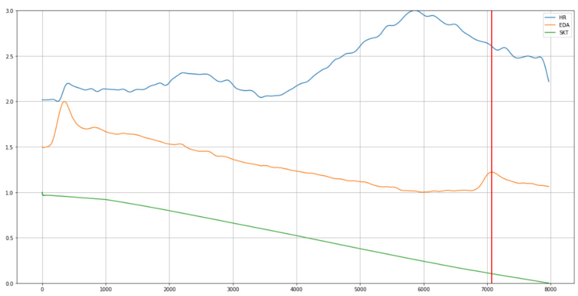
- Still pictures = IAPS film clip (iaps 04)
- Joy/Happiness = A fish called Wanda (test 22)
- Anger = American History X (test 5)
- Fear = The Blair Witch Project(test 42)
- Disgust = Trainspotting [3] (test 17)
- Sadness = The dreamlife of angels (test 14)



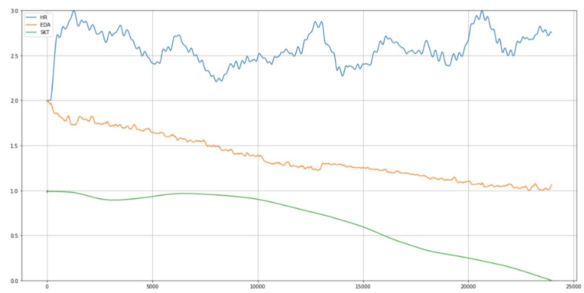
IAPS response (iaps 04)



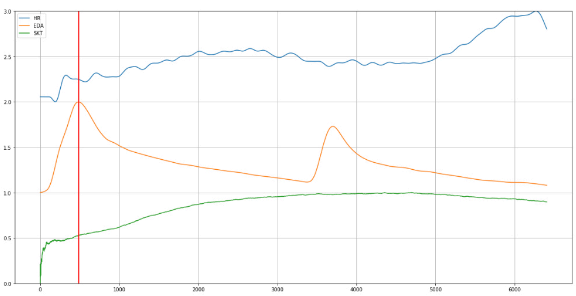
Test 22 (no OR detected)



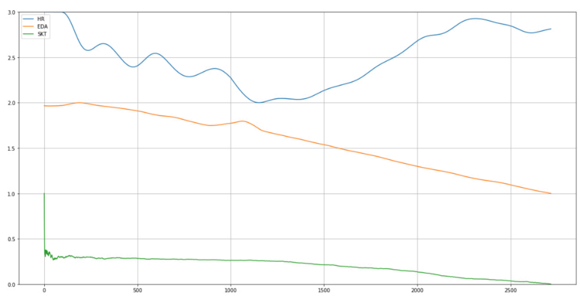
Test 05 (OR detected, Sadness)



Test 42 (no OR detected)



Test 17 (false OR detected)



Test 14 (no OR detected)

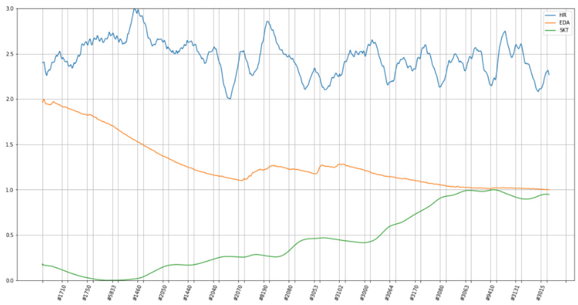
Participant number: EP5

Age: $>18 \leq 30$

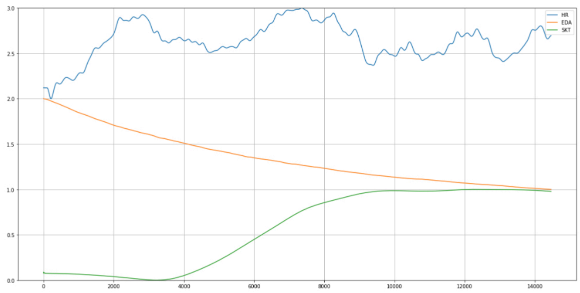
Sex: Male

Stimuli selected:

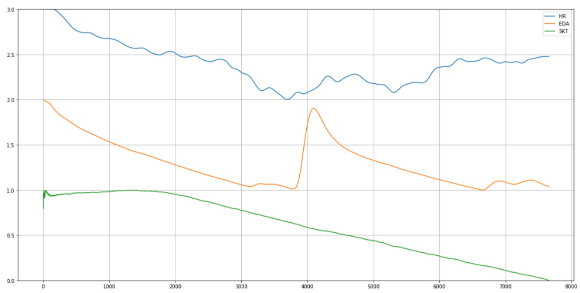
- Still pictures = IAPS film clip (iaps 05)
- Joy/Happiness = There is something about Mary [2] (test 30)
- Anger = Man bites dog [2] (test 11)
- Fear = not selected due to afraid of horror movies
- Disgust = Trainspotting [2] (test 33)
- Disgust = Trainspotting [1] (test 10)
- Sadness = Schindlers list [1] (test 18)



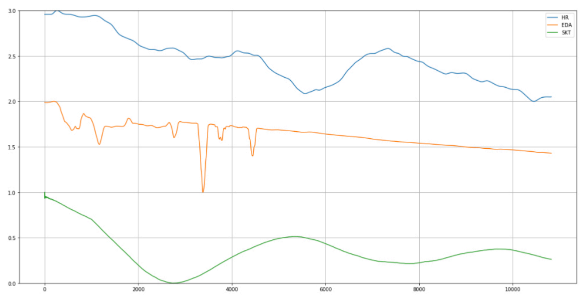
IAPS response (iaps 05)



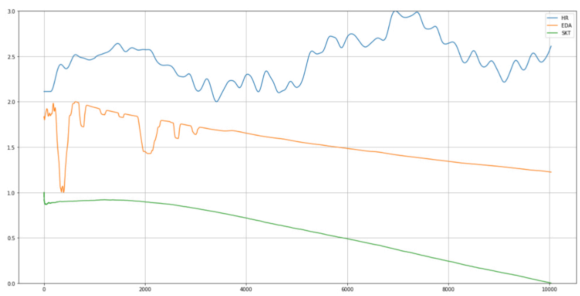
Test 30 (no OR detected)



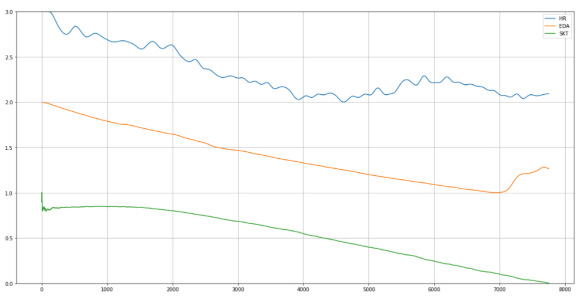
Test 11 (no OR detected)



Test 33 (unstable connection)



Test 10 (unstable connection)



Test 18 (no OR detected)

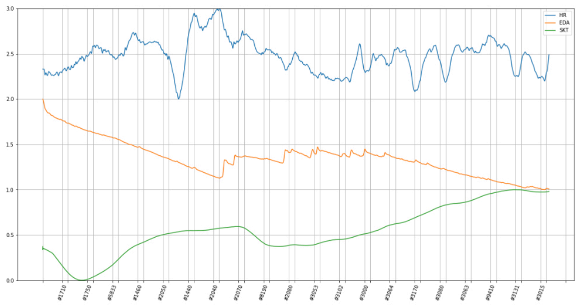
Participant number: EP6

Age: >30 $\leq$ 50

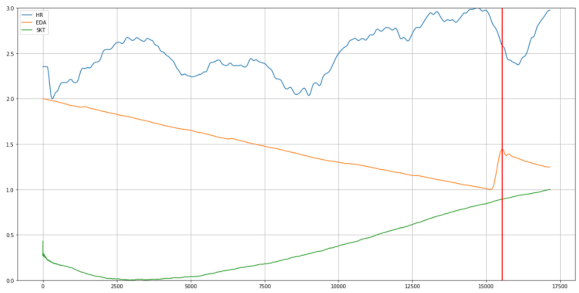
Sex: Female

Stimuli selected:

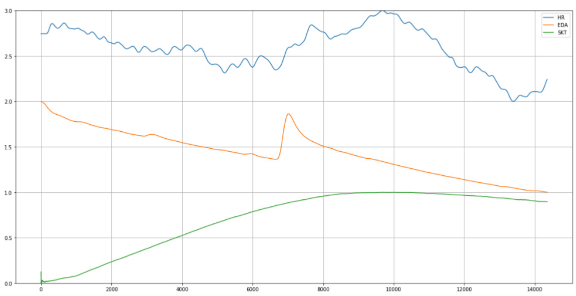
- Still pictures = IAPS film clip (iaps 06)
- Joy/Happiness = When Harry met Sally (test 15)
- Anger = Sleeper (test 25)
- Fear = The exorcist (test 24)
- Disgust = Hellrasier(test 43)
- Sadness = The Dead Poets society (test 4)



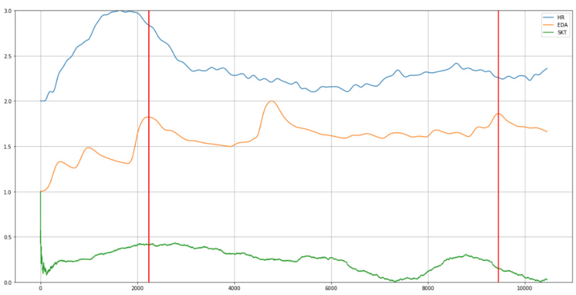
IAPS response (iaps 06)



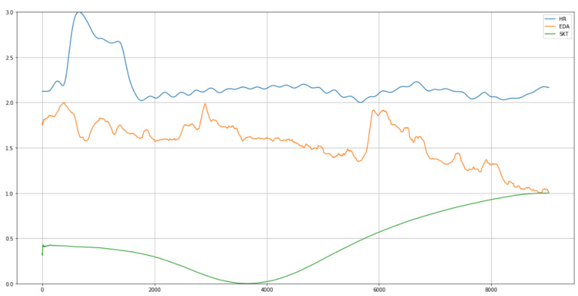
Test 15(OR detected, Joy)



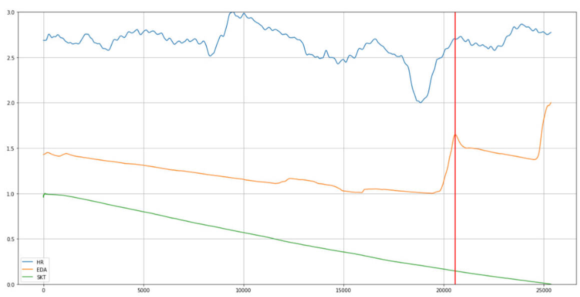
Test 25 (no OR detected)



Test 24 (2 OR detected, Disgust + Fear/Anger)



Test 43 (no OR detected)



Test 04 (false OR detection)

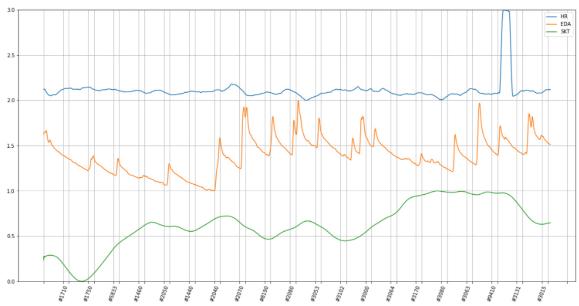
Participant number: EP7

Age: >50 $\leq$ 70

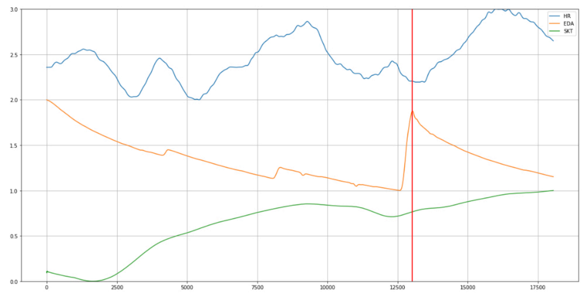
Sex: Female

Stimuli selected:

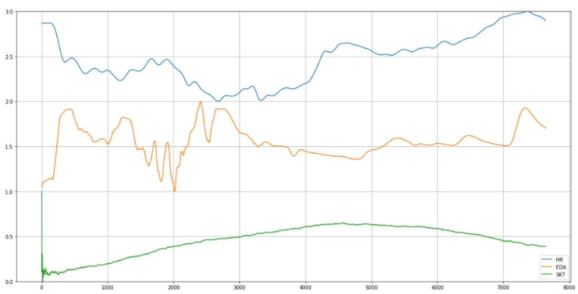
- Still pictures = IAPS film clip (iaps 07)
- Joy/Happiness = A fish called Wanda (test 23)
- Anger = Man bites dog (test 12)
- Fear = not selected due to fear of horror movies
- Disgust = not selected due to fear of disgust scenes
- Sadness = Dangerous minds (test 40)
- Sadness = Philadelphia (test 46)



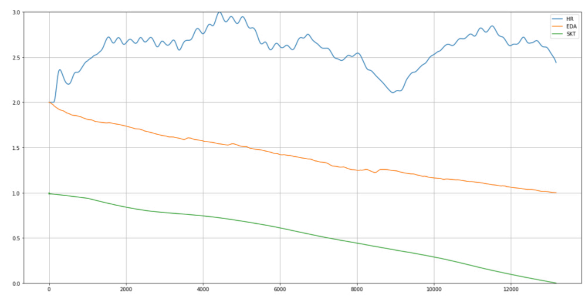
IAPS response (iaps 07)



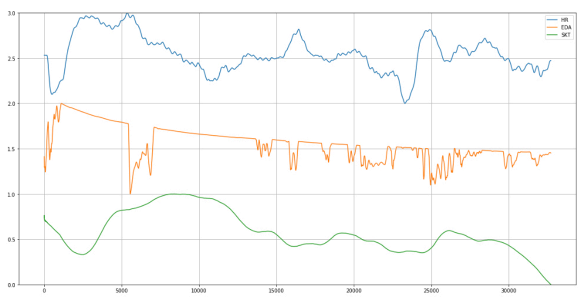
Test 23 (OR detected, Joy)



Test 12 (no OR detected)



Test 40 (no OR detected)



Test 46 (unstable connection)

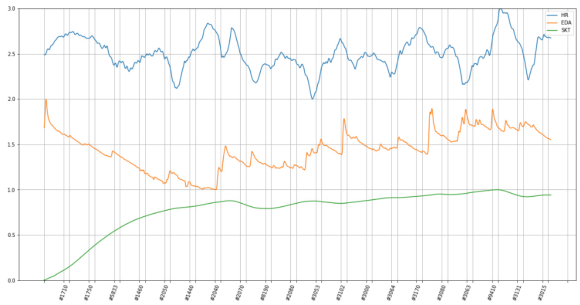
Participant number: EP8

Age: $>30 \leq 50$

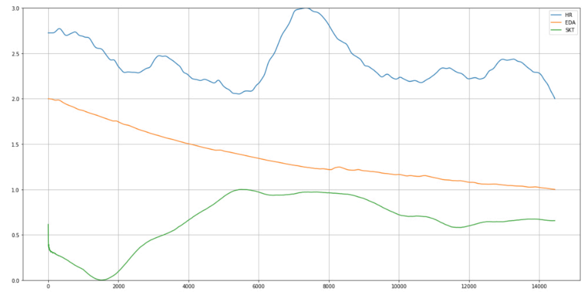
Sex: Female

Stimuli selected:

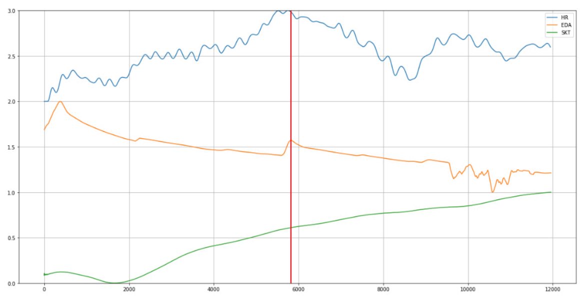
- Still pictures = IAPS film clip (iaps 08)
- Joy/Happiness = There is something about Mary [2] (test 31)
- Anger = Schindlers list [2] (test 02)
- Fear = Misery (test 37)
- Disgust = Seven [3] (test 48)
- Sadness = Dangerous minds (test 41)



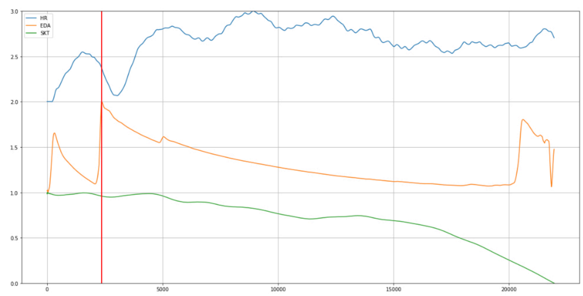
IAPS response (iaps 08)



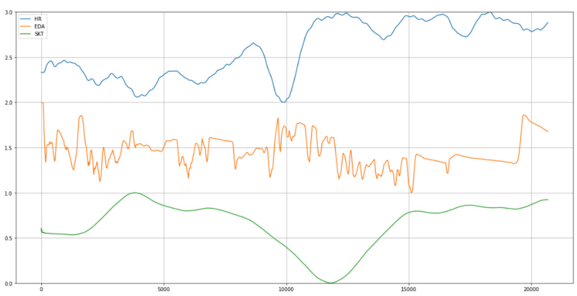
Test 31 (no OR detected)



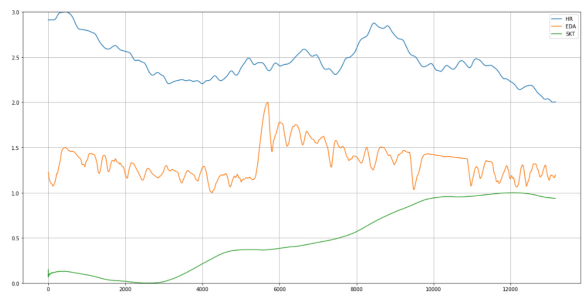
Test 02 (OR detected, Sadness)



Test 37 (OR detected, Fear/Anger)



Test 48 (motion artefacts)



Test 41 (motion artefacts)

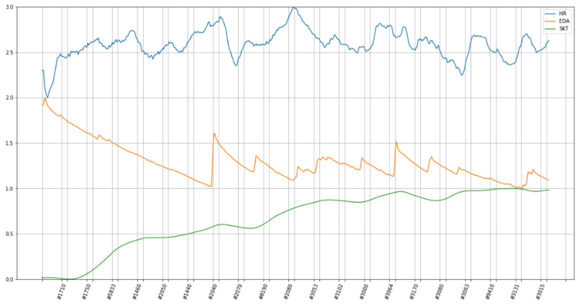
Participant number: EP9

Age: $>18 \leq 30$

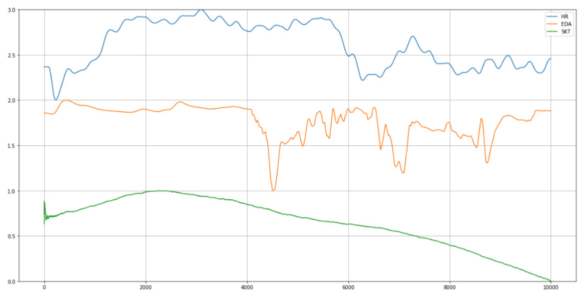
Sex: Female

Stimuli selected:

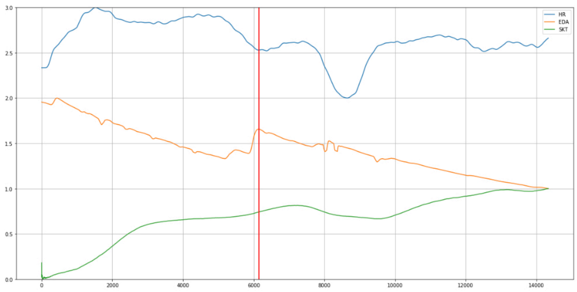
- Still pictures = IAPS film clip (iaps 09)
- Joy/Happiness = The dinner game (test 13)
- Anger = Sleepers (test 27)
- Anger = Schindlers list [2] (test 01)
- Fear = not selected due to fear of horror movies
- Disgust = not selected due to fear of disgust scenes
- Sadness = Dead man walking (test 19)



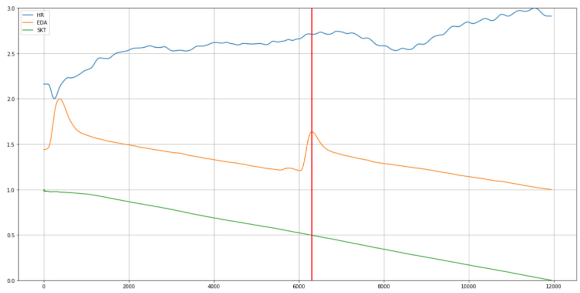
IAPS response (iaps 09)



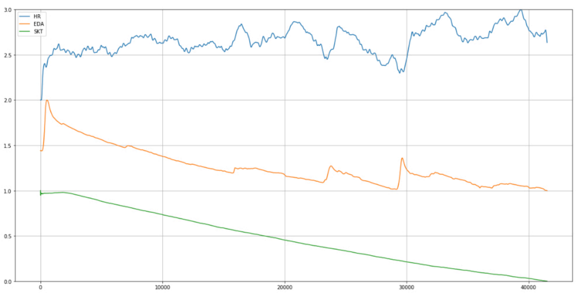
Test 13 (motion artefacts)



Test 27 (false OR detected)



Test 01 (false OR detected)



Test 19 (no OR detected)

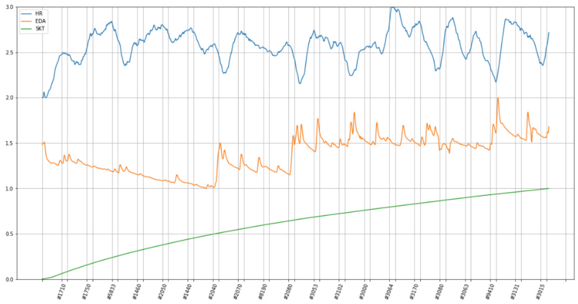
Participant number: EP10

Age: $>30 \leq 50$

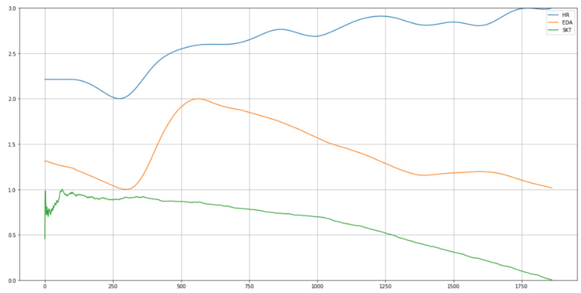
Sex: Female

Stimuli selected:

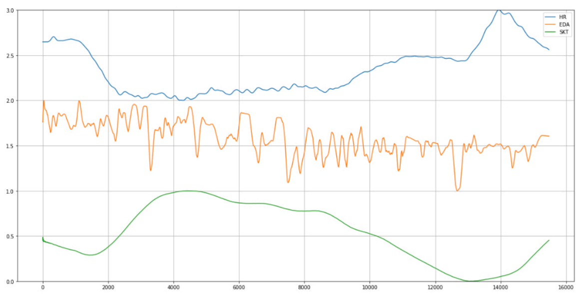
- Still pictures = IAPS film clip (iaps 10)
- Joy/Happiness = Les 3 freres (test 07)
- Anger = Leave Las Vegas (test 39)
- Fear = The Shining (test 29)
- Disgust = Hellraiser (test 44)
- Sadness = Philadelphia (test 45)



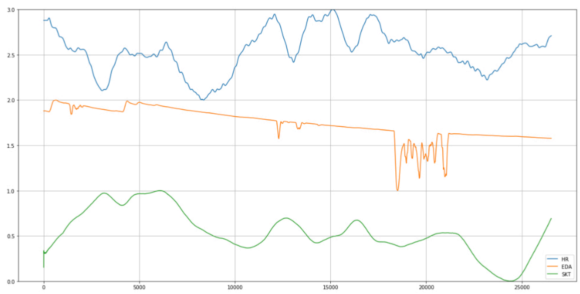
IAPS response (iaps 10)



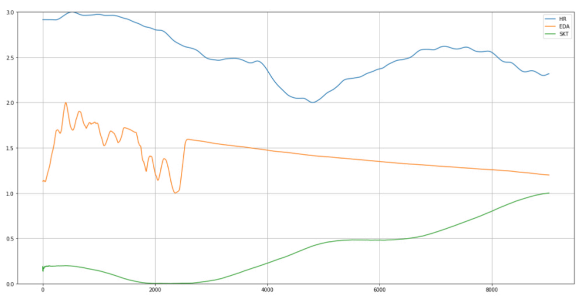
Test 07 (no OR detection)



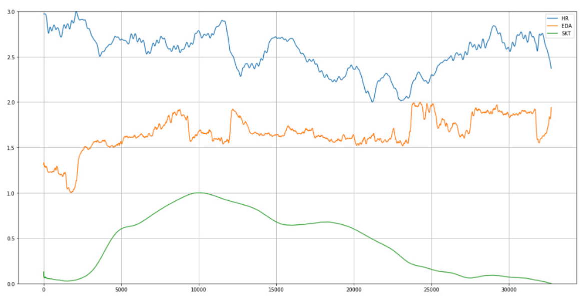
Test 39 (motion artefacts)



Test 29 (unstable connection)



Test 44 (unstable connection)



Test 45 (motion artefacts)

Appendix E

Author contributions for published papers

Three academic papers are included as part of this thesis and they are all written by multiple authors. The author of this thesis is the major and corresponding author of theses three papers and the followings illustrate the contribution of each party.

a) Major Requirements for Building Smart Homes in Smart Cities based on Internet of Things Technologies
Corresponding author: Terence K. L., Hui
Contributions: Terence K.L. Hui conceived of and prepared the manuscript. Daniel Díaz Sánchez wrote the part regarding IoT security. R. Simon Sherratt supervised the whole project and critically revised and approved the manuscript.

b) Towards disappearing user interfaces for ubiquitous computing: human enhancement from sixth sense to super senses
Corresponding author: Terence K. L., Hui
Contributions: Terence K.L. Hui conceived of and prepared the manuscript. R. Simon Sherratt supervised the whole project and critically revised and approved the manuscript.

c) Coverage of Emotion Recognition for Common Wearable Biosensors
Corresponding author: Terence K. L., Hui
Contributions: Terence K.L. Hui conceived of and conducted the experiment and prepared the manuscript. R. Simon Sherratt supervised the whole project, wrote the wearable device software and drivers and critically revised and approved the manuscript.