2017

IoT DEVELOPMENT FOR HEALTHY INDEPENDENT LIVING

Shalom Greene

Univeristy of Kentucky, sgr238@uky.edu

Digital Object Identifier: https://doi.org/10.13023/ETD.2017.200

STUDENT AGREEMENT:

I represent that my thesis or dissertation and abstract are my original work. Proper attribution has been given to all outside sources. I understand that I am solely responsible for obtaining any needed copyright permissions. I have obtained needed written permission statement(s) from the owner(s) of each third-party copyrighted matter to be included in my work, allowing electronic distribution (if such use is not permitted by the fair use doctrine) which will be submitted to UKnowledge as Additional File.

I hereby grant to The University of Kentucky and its agents the irrevocable, non-exclusive, and royalty-free license to archive and make accessible my work in whole or in part in all forms of media, now or hereafter known. I agree that the document mentioned above may be made available immediately for worldwide access unless an embargo applies.

I retain all other ownership rights to the copyright of my work. I also retain the right to use in future works (such as articles or books) all or part of my work. I understand that I am free to register the copyright to my work.

REVIEW, APPROVAL AND ACCEPTANCE

The document mentioned above has been reviewed and accepted by the student's advisor, on behalf of the advisory committee, and by the Director of Graduate Studies (DGS), on behalf of the program; we verify that this is the final, approved version of the student's thesis including all changes required by the advisory committee. The undersigned agree to abide by the statements above.

Shalom Greene, Student

Dr. Himanshu Thapliyal, Major Professor

Dr. Caicheng Lu, Director of Graduate Studies

IoT DEVELOPMENT FOR HEALTHY INDEPENDENT LIVING

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of
Master of Science in Electrical Engineering
in the College of Engineering
at the University of Kentucky
By

Shalom Greene

University of Kentucky

Lexington, Kentucky

Director: Dr. Himanshu Thapliyal, Professor of Electrical and Computer Engineering

University of Kentucky

Lexington, Kentucky

2017

ABSTRACT OF THESIS

IoT DEVELOPMENT FOR HEALTHY INDEPENDENT LIVING

The rise of internet connected devices has enabled the home with a vast amount of enhancements to make life more convenient. These internet connected devices can be used to form a community of devices known as the internet of things (IoT). There is great value in IoT devices to promote healthy independent living for older adults.

Fall-related injuries has been one of the leading causes of death in older adults. For example, every year more than a third of people over 65 in the U.S. experience a fall, of which up to 30 percent result in moderate to severe injury. Therefore, this thesis proposes an IoT-based fall detection system for smart home environments that not only to send out alerts, but also launches interaction models, such as voice assistance and camera monitoring. Such connectivity could allow older adults to interact with the system without concern of a learning curve. The proposed IoT-based fall detection system will enable family and caregivers to be immediately notified of the event and remotely monitor the individual. Integrated within a smart home environment, the proposed IoT-based fall detection system can improve the quality of life among older adults.

Along with the physical concerns of health, psychological stress is also a great concern among older adults. Stress has been linked to emotional and physical conditions such as depression, anxiety, heart attacks, stroke, etc. Increased susceptibility to stress may accelerate cognitive decline resulting in conversion of cognitively normal older adults to MCI (Mild Cognitive Impairment), and MCI to dementia. Thus, if stress can be measured, there can be countermeasures put in place to reduce stress and its negative effects on the psychological and physical health of older adults. This thesis presents a framework that can be used to collect and pre-process physiological data for the purpose of validating galvanic skin response (GSR), heart rate (HR), and emotional valence (EV) measurements against the cortisol and self-reporting benchmarks for stress detection. The results of this framework can be used for feature extraction to feed into a regression model for validating each combination of physiological measurement. Also, the potential of this framework to automate stress protocols like the Trier Social Stress Test (TSST) could pave the way for an IoT-based platform for automated stress detection and management.

KEYWORDS: Internet of Things, smart healthcare, quality of life, affective computing, stress detection, voice automation, Amazon Echo, biosensing, GSR, automated facial expression analysis

Shalom Greene

May 5, 2017

IoT DEVELOPMENT FOR HEALTHY INDEPENDENT LIVING

By

Shalom Greene

Himanshu Thapliyal

(Director of Thesis)

Caicheng Lu

(Director of Graduate Studies)

May 5, 2015

(Date)

ACKNOWLEDGMENTS

I'd be remiss not to give thanks to God Almighty
My faith in Christ helps propel success in all that I do
I'd also like to thank all those who've helped to guide me
To each one of them my respect is also due

I'd like to thank my advisory committee for all of their guidance
The advice and feedback provided has been invaluable
Individual thanks is given, lest my gratitude resides in silence
This is specifically to Dr. Allison, Dr. Dietz, and Dr. Thapliyal

Sincere thanks goes to family and friends whove always been in my corner
My family's love has garnered strength like none other
And there's nothing like a friend who's a true supporter
So, a special thanks goes to those who've supported me without border

If not for STEP at MCC, this path probably would not be
So, many thanks goes to a man named Adam Nogaj
Engineering wasn't always in my plans for me
But his advising was crucial in showing me the way

Salute to all who've been an influence to my success
Each one known and unbeknownst
With every stride I'll continue to try my best
And make sure that every step counts

A very special thanks and dedication goes to the late Bob Davis, who was a great friend, mentor, and fellow engineer.

Table of Contents

List of Figures

Chapter 1

Introduction

The internet of things has been consistently growing for the past decade and is foreseeable to continue its growth in capabilities and connectivity. IoT devices and networks have gained much of their popularity from the convenience of wireless automation. This sort of convenience is applicable to almost all industries, and it comes to no surprise that the health industry can benefit from advances in this area as well. Since the birth of the modern medical industry, medical professionals have looked to technologist to aid in the care of their patients. Technological advances in the medical field have contributed to the saving of millions of lives, which are the very technologies that have become the backbone of healthcare. Without the advent of technologies such as the pacemaker, ventilator, ECG, and the systems managing them, healthcare would not be as effective as we now know it to be today.

In effort to continue this push in advancement toward the benefit of healthcare, the research undergone for this thesis involves the use of wireless devices equipped with sensors for the purpose of detecting health-related events. In particular, a framework has been designed and developed to collect physiological data for detection of psychological stress. Additionally, an IoT-based infrastructure has been developed to detect fall events. Although fall detection devices and systems are not at all new, a new layer of interaction has been added to integrate a fall detection device within a smart environment. Namely, this is a voice interface which has been put in place to extend the capabilities of a fall detector by means of allowing actions to be taken based on verbal command. The same voice interface is employed for the aspect of the framework that collects physiological data. Physiological data collected by the framework includes galvanic skin response (a measurement of skin conductivity), heart rate, and valence (overall sentiment, such as positive, negative, or neutral) via facial expression. The framework is able to collect data from sensors simultaneously, while also being able to communicate health-related events across the connected network.

1.1 Motivation

A longstanding concern for older adults living independently has been their safety within the home and accessibility to help in case of accidental injuries. As people begin to age, physical challenges incur that either impede ability or put older adults at risk of greater health decline. Fall-related injuries have been one of the leading causes of death in older adults [1, 2]. For example, every year more than a third of people over 65 in the U.S. experience a fall, of which up to 30 percent result in moderate to severe injury [6]. Many of these injuries happen within the home [6] and the risk of major health decline due to falls can be reduced through home aid assistance technology.

The advancement of the fall detection device in its effectiveness is of utmost importance, which includes the usability of the device. An IoT-based fall detection system can be integrated within smart home environments and smart facilities to increase safety and quality of life of older adults [7, 8]. The use of smart devices such as smart cameras, smart wristbands and voice activated devices can greatly enhance the convenience and effectiveness of a fall monitoring system.

However, as sophistication grows in the development of aid devices, there is also a growing demand in the ease of use for these devices by the end user. Rapid growth of technology has created a gap between younger and older populations in understanding how to use the technology. Therefore, a significant portion of this research involves the use of voice as a controller. Voice is a natural interface that is common to most people. There is very little learning curve involved in the use of speech as a tool to invoke activity. A major goal of this research is to leverage voice to help lessen the gap between the complexity of technological design and its simplicity of use when considering health related technology. Thus, an IoT infrastructure and stress detection framework have been developed throughout the course of this research to help close this gap. These developments aim to offer some complexity in design while also providing a more natural and non-invasive, health-centered interface than what has been traditionally in use.

Along with the physical concerns of aging, there is also growing concern for psychological health. Regarding normal young and middle-aged adults, psychological health is of great concern when considering demanding tasks at work, at school, and other social settings. Also, as multitasking has risen to be a norm, juggling tasks left and right, stress has also risen along with it. Concerning aging populations, psychological decline with age has been tied to serious illnesses such as Alzheimers disease and and other forms of dementia [3]. Though these illnesses are aggressive and no definite cure has yet been discovered, there is a precursory state between normal aging and dementia that has risen more in concern due to possible prevention of its progression into a more serious illness. This intermediate state is called Mild Cognitive Impairment (MCI), which involves complications in executive functions such as memory, language, thinking, and judgment. Studies have shown that those with MCI who undergo a lot of psychological stress have a greater chance of developing dementia [3]. Thus, if stress can be measured, there can be countermeasures put in place to reduce stress and its negative effects on psychological and physical health. So, it is a motivation of this research to produce a framework that can aid in collecting measurements of the physiological manifestations of psychological stress, as well as aid in paving way for launching intervention based on detected stress.

Not many systems are in place to effectively detect a persons stress level in a non-invasive manner. However, much research has taken place in the technology that can be used for detecting stress. An entire field of computing, affective computing, has been dedicated to the use of biological sensors to determine emotion. The same technologies employed for detecting emotions, which are products of psychological state based on a given stimulus that affects physiological, behavioral and cognitive change, can be applied to the detection of stress as a psychological state.

Additionally, this research captures personal interest for me because of my experience working in a nursing home. Witnessing firsthand the difficulties that older adults face as they age has influenced me to dedicate my thesis to aiding in the development of systems for their benefit.

1.2 Contribution & Significance

The objective of this thesis is to address the following issues:

- ▷ Usability of technology for the elderly and those not technologically savvy
- ▷ Integration of fall detection within a smart facility
- ▷ Automation of Trier Social Stress Test (TSST) protocol for assessing stress
- ▷ Automated stress detection for stress intervention

This thesis places specific emphasis on the use of voice as a tool for command and automation. This is quite significant in its impact on usability, especially as it pertains to those who are not technically savvy. Allowing for a voice interface to be used as an abstraction layer for automation gives the user greater confidence in interacting with the system by lessening the complexity of operation. Also, by adding voice automation a natural interaction model is able to be adapted to fit the needs of the user. Most fall-detection systems currently available are not voice controlled which can result in significant amount of learning curve, does not allow remote monitoring, and can generate significant false positive calls to the primary caregivers.

◊ *The first contribution of this thesis is to overcome some of the limitations of existing fall detection systems by proposing an infrastructure surrounding IoT-based fall detection for smart environments that not only sends out alerts, but also employs voice as the primary controller for invoking action. Such connectivity could allow older adults to interact with the system without concern of a learning curve.*

◊ *This second contribution of this thesis is the integration of fall detection within a larger IoT infrastructure which allows for automated actions based on detected falls. Fall detection can invoke crucial functions in security and communication such as camera monitoring, phone calling, and texting. The proposed infrastructure for IoT-based fall detection will enable family and caregivers to be immediately notified of the event and remotely monitor the individual. Integrated within a smart home environment, the proposed IoT-based fall detection system can improve the quality of life among older adults.*

The non-biological, and perhaps first, benchmark for stress testing has been self-reporting. As it is possible for someone to be misleading about their psychological stress state, perhaps due to confusion, another more definitive measure is demanded, which is why many modern stress tests use biological measurement for discerning stress. Many stress tests of the past couple decades rely on biological samples such as saliva or serum (blood) sampling for cortisol measurements. These biological means of measurement have long been the benchmarks for gathering information on stress; however, they are invasive in nature. A goal of this research was to create a framework that could be used to pave way toward a non-invasive method of determining psychological stress. So, instead of the cortisol measurements, a non-invasive physiological approach is taken to obtaining stress measurements via electrodermal activity, cardiac activity, and facial expression analysis.

◊ *Another contribution of this research is the potential of this framework to be used to automate, or even replace, stress protocols like the Trier Social Stress Test (TSST) [4]. This thesis presents a framework that can be used to collect and pre-process physiological data for the purpose of validating galvanic skin response (GSR), heart rate (HR), and emotional valence (EV) measurements against the cortisol and self-reporting benchmarks. The results of this framework can be used for feature extraction to feed into a regression model for validating each combination of physiological measurements.*

Traditionally, the TSST Protocol, which is the benchmark protocol for measuring psychological stress, relies on saliva cortisol measurements [4]. Unfortunately, cortisol measurements have an average 20-25 min delay in response from stimuli to presence in saliva [5]. Hence, also considering the time involved in analyzing the salivary sample, no foreseeable real-time solution can be built off of salivary cortisol measurements. Also, automation would be slightly more complicated for assessing such a biological measurement. Providing such a real-time solution allows for smoother automation of responses to stress as detected by physiological measurements.

◊ *The final contribution of this thesis is to offer a means of real-time response to psychological stress. In addition to providing pre-processed data for regression analysis, the framework presented here also provides a means for real-time response to stress based on GSR, heart rate, and emotional valence. This research paves a way for generat-*

ing real-time intervention to psychological stress based on non-invasive physiological measurements.

1.3 Outline of Thesis

The remaining chapters of this thesis is organized in the following fashion: Chapter 2 as a discussion on background information; Chapter 3 as a discussion of the IoT infrastructure for promoting health independent living; Chapter 4 as a discussion on the framework as it pertains to stress detection; and Chapter 5 as a conclusion. Chapter 2 provides some background information necessary in understanding the technology used in this research. This includes information on how physiology relates to emotion and stress, and an explanation as to why certain biosensors were chosen for this research. Chapter 3 discusses the infrastructure put in place for voice automated IoT-based fall detection. This is the basis for the physical health portion of the framework. Chapter 5 discusses the larger scale of the framework that is based on physiological measurements for psychological stress detection. This forms the basis for the psychological health portion of the framework. Chapter 5 then concludes with the impact of the presented framework and how it contributes to further research in the physical and psychological health domain.

Chapter 2

Background and Related Work

2.1 Background on IoT-Based Fall Detection

This section will explore the major components of the IoT-based fall detection system developed for this thesis. This includes background information on accelerometers, Amazon Echo and the Alexa Voice Service, and the Raspberry Pi used for this research.

2.1.1 Sensing Acceleration via ADXL345 Accelerometer

The core of most common fall detection systems is the use of accelerometers to determine the acceleration of an object. Acceleration is the measure of change in velocity over a period of time. Velocity is measured in meters per second (m/s), including the direction of motion. Hence, acceleration is measured in meters per second squared (m/s^2). Accelerometers measure acceleration in one of two modes: statically or dynamically [81]. Static acceleration is acceleration due to gravity which is primarily used for tilt and orientation sensing. Dynamic acceleration is acceleration due to active movement. Typically, fall detectors primarily focus on dynamic movement, as this is most evident in sensing falls. However, static acceleration is often used to determine orientation of the device wearer to understand if the wearer is standing, sitting upright, reclining, or laying down [79]. This information, combined with the dynamic acceleration, can be useful in determining whether the device wearer has sustained an injurious fall.

Accelerometers use whats called MEMS (microelectromechanical) technology to sense acceleration via electromechanical sense circuitry. This circuitry usually surrounds either capacitive or piezoelectric elements. Capacitive accelerometers use differential capacitors that sense voltage changes between capacitive plates. Piezoelectric accelerometers operate based on the transduction properties of piezoelectric materials. Piezolelectric material used in accelerometers are typically crystalline structured ceramic (commonly Lead zirconate titanate aka PZT) that convert mechanical energy into electrical energy [82]. This transference of energy allows for the accelerometer to sense movement. In both types of MEMS accelerometer, the voltage sensed is converted to units of g-force (force of gravity) for acceleration [81].

In addition to sensing acceleration and orientation, accelerometers also can be used to measure rotation, shock and vibration. The sensor used in this research is a 3-axis accelerometer that is capable of sensing all five of the mentioned modes of sensing. However, only two (acceleration and shock) are employed in the development of the fall detector used in the proposed system. The fact that the sensor is 3-axis, means that the sensor can detect acceleration along the x-, y-, and z-axes in both directions. This is helpful in determining the direction of fall. It is very typical to use more than just the acceleration to determine falls. Hence, features like rotation, orientation, and shock are also employed to help increase the accuracy of fall detection. This is evident in many research studies (see section *Related Research in Fall Detection* for examples).

2.1.2 Voice Command via Amazon Echo and Alexa Voice Service

The IoT-based fall detection system presented in this research employs the use of a voice interface enabled by the Amazon Echo and Alexa Skill Kit. The Amazon Echo is a personal aid device that is capable of listening and responding to voice commands. The device is primarily a housing for a speaker system and microphone array, with a small processing unit for wireless communication. The Amazon Echo is wirelessly connected via Wi-Fi and Bluetooth. Bluetooth is used to initially pair your smartphone to the Echo via the Alexa App, in which the user must then use that connection to establish an internet connection over the nearby Wi-Fi network. Additionally, the Bluetooth connection allows for direct audio streaming and voice control to connected smartphones [83]. Though the Amazon Echo can handle voice input and output, the actual voice recognition is handled by Alexa Voice Service (AVS), which is a cloud-based voice recognition software [84]. Voice commands are created via the Alexa Skill Kit (ASK), which grants access to APIs, tools, documentation, and code samples pertinent to AVS.

The Alexa Skill Kit allows developers to create skills (voice activated actions) via the development of three major components: intent schema, Lambda function, and sample utterances. The intent schema is a JSON formatted file that defines each intent used in the skill. An intent is composed of an identifier (name) and any slots that possibly belong to the intent. Slots are any variables (number, text, or custom datatype) that are expected to be interpreted from voice and used as values within a Lambda function. A Lambda function is a collection of files that describe how intents are handled; directing any actions taking place based on those intents and their associated slots. The last component, sample utterances, is just a text list of intent names with associated utterances that can be used for invoking each intent. Once these three components are in place, the Alexa Skill Kit can invoke AVS to connect voice commands to their intended action.

2.1.3 HTTP Servicing via Raspberry Pi

Another major component of the IoT infrastructure for fall detection is the connectivity of devices using HTTP communication. HTTP (hypertext transfer protocol) is an internet protocol commonly used for webpages for servicing web requests. Each HTTP request is handled as either a GET or POST request. A GET request simply asks the hosting server for information, in which the server would provide a response containing the requested data. Instead of requesting data from the server, a POST request is used to provide the server with data, in which a simple response of success or failure of data reception is provided back to the requester. Simple HTTP networks are composed of a host server that has a list of URL (uniform resource locator) paths, which represent the possible resources that can be accessed, and endpoints that connect to the server for request posting.

HTTP servers can be implemented on any computer machine that has access to the internet and the software means of programing a HTTP connection. Programming languages such as Javascript, NodeJS, Python, and C++ can be used for programming such a server. For this research a Raspberry Pi running NodeJS was used for creating the HTTP server. The Raspberry Pi is a low-cost, full-functioning miniature computer that leverages Python programming language as its official programming language. However, this does not mean that Python is the only language that can be used. In fact, the Raspbian operating system (official operating system of Raspberry Pi) is largely based on the Debian version of Linux, which is heavily based on C language programming. The actual programming language used for programming the server was NodeJS, which is a language heavily used for web based programming.

2.2 Related Research in Fall Detection [86]

Medical home alert systems developed to assist older adults within their own home date as far back as the early 1970s with the advent of the first personal emergency response system (PERS) created by German inventor Wilhelm Hormann [9]. The medical home alert system was a dedicated phone line for the sick and elderly to contact someone for help. Hormann called the system Hausnotruf, which translates to home alert in English. This idea was shortly thereafter improved upon by California based company American International Telephone Company who created the Emergency Dialer, which added more portability via a pendent that is worn around the neck [9].

Several interesting contributions in the area of fall detection have added to medical home alert systems since t he advent of Hausnotruf. Several illustrative examples from the past 20 years are discussed in this section. The examples illustrated here are not a comprehensive list of fall detection system within the last 20 years, however, we choose to review these systems based on their relevance to the research undergone for this thesis.

For example, in 2004, a combined effort between InfraRed Integrated Systems, Ltd. (IRISys) and the University of Liverpool developed a smart, non-contact sensor for fall detection [10]. The system used infrared imaging to detect activity and inactivity. What was good about the system was that it did not require the person to wear any special equipment. However, the detection was non-specific to who was in the room and was in need of care in the case of a fall. A larger issue in the system was that it had a high false negative rate, missing 64.3% of the falls that should have been detected.

In 2006, a European Community driven project with collaboration between universities in Spain, France, and Greece produced an automated fall detection system with a reported 90% confidence in reliability [11]. This system is accelerometer based, in which activity data is constantly recorded and reported to a call center in 24 hour intervals. The system also included GPS and GSM (Global System for Mobile communications), a European mobile voice and data service, to establish user localization and communication with a community call center. The system reportedly performs well. However, it does not have any integration within a smart home environment, nor does it integrate a means of voice communication.

In 2009, a cohort of researchers from UCLA designed a smart fall detection system called SmartFall based on a previously designed SmartCane fall detector [12]. This system, unlike most fall detection systems at the time, uses a subsequence matching algorithm to detect falls. This means that the system detects pre-fall, impact, and post-fall activity in order to correctly identify a fall. The SmartCane incorporates multiple low cost sensors, such as pressure sensors on the grip and bottom of the cane and wireless inertial sensors (3D accelerometer and 3D gyroscope) located at the crook of the cane. These allow for wireless and non-wearable, unobtrusive fall detection. This falls into a category known as Pervasive yet Non-Invasive (PNI) sensing. Results from the testing of the system range from 93.3% to 100% based on fall type. Free-fall and forward fall exhibited the best performance of 30 falls per trial from three individuals ranging in ages 25 to 35 (in which there was one individual per trial). Results from backward and side falls only suffered a cumulative three failures for fall detection among all trial participants. However, the system relies primarily on the use of the SmartCane which is inaccessible while in the shower and in the case of falling from a sitting or lying (bed) position.

In 2014, researchers from the Institute of Biomedical Engineering at the National Yang-Ming University published their work on improving elderly telecare (automatic and remote monitoring of real-time emergencies), which primarily focused on fall detection [13].

An interesting feature that this system offers is the use of Received Signal Strength Indicator (RSSI) on ZigBee devices to determine faller position. Additional to this feature, the system is actually geared toward integration into a smart home environment. The system uses ZigBee devices (which are RF based wireless devices) placed in several areas around the home to calculate position based on which device is closest to the wearable fall detector. According to the reported results, the fall detection algorithm employed has an accuracy of 88.62%, precision of 88.6%, sensitivity of 95.63%, and specificity of 73.5%. The system appears to distinguish well between falls and activities of daily living (ADLs). ADLs are normal activities such as walking, sitting, and lying down.

Also in 2014, research primarily out of Nanjing University of Information Science & Technology in China produced an enhanced fall detection system for elderly people [15]. The system detects falls by employing an accelerometer and a cardiotachometer to record acceleration, tilt position and heart rate. It utilizes consumer home networks such as IEEE 802.11, Bluetooth and ZigBee to communicate between devices on a mesh network. Sensor nodes (i.e. accelerometer, cardiotachometer, etc.) communicate either to a base station or fixed access point. Fixed access points are in place to relay signals to a base station. Base stations are used to communicate to the outside world for alerting caregivers, relatives and the ambulance in case of a dire fall. This fall detection system achieved a high accuracy of 97.5%, a sensitivity of 96.8% and a specificity of 98.1%. However, the limitation of the system appears to be in the heavy reliance on ZigBee communication. Although ZigBee is a very low power transmission protocol, it cannot transmit signals through standard construction walls. Therefore, multiple access points and base stations are needed to deploy a multiple room setup, which adds a great deal to the number of components within the system.

Most recently in 2016, collaboration between Beijing University of Technology and Beijing Engineering Research Center for IoT Software and Systems has brought about an automated fall detection system based on inertial sensors (3D accelerometer and 3D gyroscope) geared toward older adults [15]. In addition to the inertial sensors, the system included software running on a smartphone which connected via Bluetooth to the inertial sensors and used 3G wireless data to provide call and SMS messaging. Using a smartphone also allows the leverage of its GPS service. The system was able to obtain accuracy in fall detection ranging from 94 to 100 percent based on the four fall experiments that were conducted across 15 adults ranging from ages 20 to 45. Although the results from the Beijing research proved very well, the system largely relies on the smartphone as its center of processing. This is a potential issue as many older adults above 65 may not know how to operate a smartphone and as a result may not keep track of the phone. Further, allowing the phone to run out of battery power disables the entire system.

All of these systems mentioned have some level of integration of sensing and wireless technology. However, none offer a solution for an IoT enabled smart facility, particularly with a voice interface. The novelty of the proposed solution for fall detection in this paper will be to provide modularity and a voice interface in addition to internet connectivity for a fall detector within a smart home environment.

2.3 Background on Stress Detection [87]

Managing stress is a major health concern for populations around the world. Stress exists in two main forms: acute and chronic. Everyone experiences stress at some point in their life, most commonly as acute stress. Per the American Psychological Association, acute stress is the result of demands and pressures of recent past, as well as those anticipated in the near future [16]. This can come from instances such as athletic challenges, test taking, or anxiety from meeting new people. Chronic stress, on the other hand, is due to long-standing pressures and demands such as those experienced due to socioeconomic conditions, difficulties in interpersonal relationships, or an unsatisfying career [16]. If left unmanaged, it can have detrimental consequences to those experiencing it. Psychophysiological stress can manifest into physical and physiological symptoms that can affect one's health if the stress becomes chronic [16, 17]. These symptoms can be measurably observed in numerous ways, that this survey will explore. Much focus is put on acute stress as this allows researchers to study the short term effects of stress which are more easily observable. Also, due to the short-lived nature of acute stress, there is an expected lower risk to the research participant when stress is induced for the purpose of research [16]. However, extrapolating from current data, more needs to be discerned to look at the effects of long term stress.

Stress, whether chronic or acute, has effects on physical condition. In acute stress, symptoms may include emotional distress, muscular ache and tension, digestive tract issues, and over-arousal [16]. The more serious of these concerns relate to over-arousal, which can lead to heart attacks, arrhythmias, and possible sudden death in those with pre-existing heart conditions [18]. Less serious concerns include headache, back pain, heartburn, stomach ache, elevated blood pressure, and rapid heartbeat [16]. Chronic stress can exhibit the same symptoms as acute stress, but with more extensive damage. Chronic stress is identified as a risk factor for hypertension and coronary disease [18, 19], irritable bowel syndrome (IBS) and gastroesophageal reflux disease (GERD) [20], as well as generalized anxiety disorder and depression [21]. If chronic stress is allowed to proliferate, the ongoing symptoms may reduce the quality of life of those experiencing this stress.

Early stress detection methods relied heavily on self-reports in response to a standardized list of questions. Examples of these early methods include the Perceived Stress Scale (PSS-10 or PSS-14) and the Depression Anxiety and Stress Scale (DASS-21), which were based on questionnaires regarding life events [22]. Even though these methods have been validated, there is still the concern of subjective response bias from the individual that may introduce additional skewness into the assessment of stress. Hence, there is a need for objective measures with basis in physical and physiological domains. Since stress also presents itself via biomarkers and physical expression it can be measured objectively and observed.

The classic standard for physiological measure of stress has been assessment of cortisol levels produced by the hypothalamic-pituitary- adrenocortical (HPA) axis. This assessment involved cortisol extractions from various sources: hair, saliva, blood (serum), and urine sampling. These measurements were invasive and/or involved a laborious process for analysis [23, 24]. Hence, discovery of alternative means of measurement via wearable, as well as non-contact, sensors has been developed and are now more commonly used. Predominant traditional methods of measuring stress include the use of electrocardiography (ECG) and electroencephalography (EEG). However, the current trend in affective computing, particularly in stress detection, is leaning more toward non-invasive methods of measurement dealing with skin conductance and photoplethysmography (optical sensing).

2.4 Background on Stress-Based Affective Computing [87]

Affective computing is a rising field of interest as more and more people are becoming aware of the association between health and emotional states. Affective computing is the use of both hardware and software technology to detect the affective state of a person. It is an active research area that has seen much growth in technology geared toward affective state analysis. Its origin is accredited to Dr. Rosalind Picard of MIT when she published her 1995 paper on affective computing [25]. It has since become a modern branch of computer science for human-computer interfaces (HCI) [26, 27]. This stem of computer science has two main veins: (1) detection and recognition of emotional information and (2) simulation of emotion in computational devices. The focus of the current survey will be the detection and recognition of emotions as affective states.

Affective states are psychophysiological constructs that influence behavior. These constructs are generally divided into three categories: arousal, valence, and motivational intensity [28]. Most technology related research in affective computing surrounds arousal because of its objective measurement of physiological activity. Arousal is directly tied to the autonomic nervous system (ANS) for which it can be measured in numerous ways via physiological sensors. Measuring arousal enables the assessment of both valence and motivational intensity of emotions to influence human behavior. Valence is the rating of positive, negative or neutral affect, while motivational intensity is the measure of how likely an affect will elicit activity in response to the stimuli presented to the individual.

The technology used in affective computing exploits both physiological and physical manifestations of one's affective state to determine their current emotion. There are six basic emotional states deduced in affective computing: joy, anger, surprise, disgust, sadness, and fear. Other affects such as frustration and stress can also be computed from these six basic emotional states.

The physiological measures of stress and their corresponding technologies can be classified as follows:

- ▷ Brain activity → Electroencephology (EEG)
- ▷ Heart activity → Electroencephalography (ECG)

- ▷ Skin Response → Galvanic Skin Response (GSR)/electrodermal activity(EDA)
- ▷ Blood activity → Photoplethysmography (PPG)
- ▷ Muscle activity → Electromyography (EMG)
- ▷ Respiratory Response → Piezoelectricity / Electromagnetic generation

Physical measures of stress and their corresponding technologies can be classified as follows:

- ▷ Facial expression → Automated facial expression analysis (AFEA)
- ▷ Eye Activity → Infrared (IR) eye tracking
- ▷ Body Gesture → Automated gesture analysis (leveraging AFEA)

2.5 Physiological Stress-Based Affective Computing [87]

There are several indicators that provide physiological measures of stress. The most prevalent include: heart activity (ECG), brain activity (EEG), skin response (GSR/EDA), blood activity (PPG), respiratory response (piezoelectricity & electromagnetic generation) and muscle activity (EMG). Each of these will be examined more closely in the following sections.

2.5.1 Heart Activity & Electrocardiography

1) Heart Activity

A predominate factor examined for stress across many studies involve heart rate and heart rate variability. When stress is induced in an individual, their heart rate is elevated. This is all in part of the fight-or-flight response that is often referenced to high stress situations. Heart rate variability (HRV) provides additional information than heart rate alone. HRV is the measure of standard deviation in inter-beat intervals of successive R waves in a heartbeat [29]. A typical heart beat consists of four main components: the baseline, P wave, QRS complex, and T wave. The R spike of the QRS complex is most commonly used for evaluation of HRV as it is the most predominant spike in the waveform [30].

In stress situations heart rate variability is a product of change in autonomic nerve activity which is composed of sympathetic and parasympathetic modulation. The function of the sympathetic nervous system (SNS) as it relates to the heart is to speed the heart rate to provide an increase in blood supply to the body. This queues the fight-or-flight rush that comes with stress. After the stressor has been removed, the parasympathetic nervous system (PNS) begins to slow the heart rate. Examining the relationship of these two nervous systems provides insight on the stress state of an individual [29, 31]. HRV provides such insight. The waveform of a heart captures both activity and HRV further enables the analysis of the activity across multiple heart beats. This allows for monitoring of how quickly the body responds to stress, how long the stress response lingers after the stimulus, and how rapidly the PNS can act to reduce stress. When combined with other methods of stress assessment, HRV can pinpoint corresponding physiological and physical markers associated with stress in an individual.

2) Electrocardiography (ECG/EKG)

One of the most heavily used stress detection methods employs the use of ECG (alternatively appearing as EKG) for heart activity such as heart rate (HR) and heart rate variability (HRV). ECG units use electrodes that are strategically placed on the body to measure electrical signals produced by the depolarization and repolarization of the heart

[32]. There are a few different configurations of this set up based on ECG lead polarity and electrode placement. The most common configuration is the standard limb, bipolar lead setup illustrated in *Figure 2.1(a)*. *Figure 2.1(b)* shows the Eithoven Triangle that translates the lead placements to axial references in the electrical signals being recorded by each electrode.

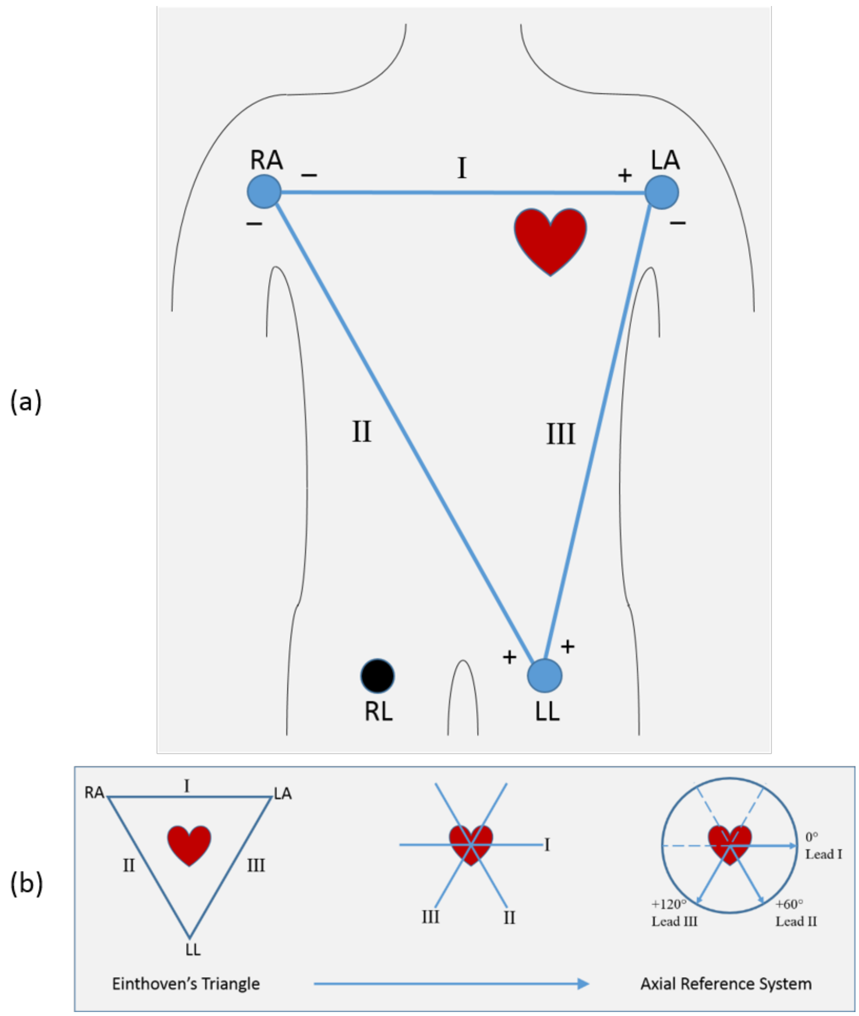

Figure 2.1: ECG Instrumentation. (a) ECG standard limb, bipolar lead setup instrumentation; (b) Einthoven's Triangle & ECG Axial Reference [32]. RA = Right Arm (negative node), LA = Left Arm (bipolar node), LL = Left Leg (positive node), RL = Right Leg (ground reference)

The HRV data extracted from ECG measurements can be filtered by frequency content and then analyzed. The frequency content is generally broken down into 2 bands: low-frequency (LF) vs high-frequency (HF), with LF being 0.04-0.15 Hz and HF being 0.15-0.4 Hz [33]. It also may be common to see three frequency bands in which there is a low-frequency (0-0.08 Hz), mid-frequency (0.08-0.15 Hz), and high-frequency (0.15-0.5 Hz) [34]. Alternatively, these may be labeled as very low-frequency (VLF), low-frequency (LF), and high-frequency (HF), respectively. This separation of frequency content is useful since sympathetic (SNS) activity is associated with low frequency content, while parasympathetic (PNS) activity is associated with high-frequency content [33]. The analysis involved in assessing HRV lies in the energy ratio of low-frequency to high-frequency content. Or in other words, the ratio of sympathetic to parasympathetic activity. This is usually modeled as

$$PowerRatio_{ECG} = \frac{Power_{LF}}{Power_{HF}}$$

[34].

The power values are typically extracted from power-spectral density (PSD) which employ fast-fourier transforms (FFT) to convert time domain data into frequency domain data [33]. Alternatively, power densities may be normalized to total power using the following models:

$$TotalPower_{LF} = \frac{Power_{LF}}{Power_{HF} + Power_{LF}} \times 100$$

and

$$TotalPower_{HF} = \frac{Power_{HF}}{Power_{HF} + Power_{LF}} \times 100$$

[33].

ECG is the current golden standard for monitoring heart activity.

2.5.2 Brain Activity & Electroencephalography

1) Brain Activity

The brain is the epicenter of all nerve stimuli. Thus, monitoring brain activity is complimentary to detecting stress response. Stress response originates in the amygdala, which communicates with the hypothalamus to initiate the autonomic nervous system (ANS) response [35]. This stimulation of the ANS provokes subsequent physiological and physical manifestations of stress. Evoked potentials at the cerebral cortex correspond to the signals sent between the amygdala and hypothalamus, which allows recording of brain activity at the scalp [36]. Specifically, the frontal cortex is examined, usually by means of electroencephalography (EEG).

2) Electroencephalography (EEG)

For direct brain activity, there are several different technologies used for measurements, including positron emission tomography (PET), functional magnetic resonance imaging (fMRI) and electroencephalography (EEG). PET and fMRI both use blood flow as indicators of brain activity, whereas EEG uses electrical potentials. Though both PET and fMRI are effective means for measuring brain activity with high spatial resolution, both are very slow in response and involve expensive equipment [37]. Therefore, our focus here will be on EEG technology.

EEG measurements involve a matrix of electrodes placed on the head that record event related potentials (ERPs) upon the occurrence of brain stimulation. These electrodes are most commonly fitted into a cap according to the international 10/20 system. This system is based on 19 electrode placements spaced at 10 and 20 percent intervals across the cranium. Each percentage is of the total length of the cranium either front-to-back or ear-to-ear. The Nasion (bridge of the nose) and Inion (occipital protuberance) are used as the boundary markers for the perimeter of the electrode system. [38]. The system is used to allow comparison of results from research conducted all over the world [37-38]. *Figure 2.2* shows the top view of the 10/20 system. Also, see the caption for more details on electrode labeling.

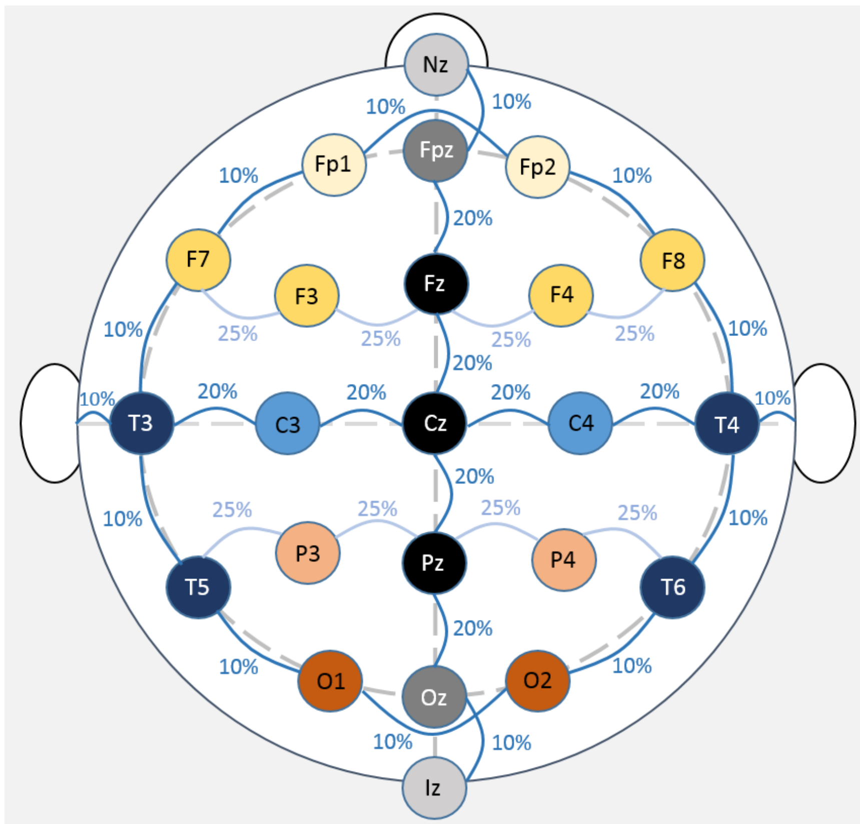

Figure 2.2: **Top view of the 10/20 system EEG electrode placement.**
Electrode Lobe Mapping: F = Frontal[1], T = Temporal, C = Central[2], P = Parietal, O = Occipital. Boundary references include the Nasion (N) and Inion (I). Odd numbers correspond to the left hemisphere, while even numbers correspond to the right hemisphere. The 'z' markings represent zero reference points. The lighter colored arcs between electrodes represent additional placements that are typically added to the standard 19 electrode system.

Similar to the ECG analysis, measurements are filtered into frequency bands and can be analyzed according to power spectrum. This is called the power spectrum ratio technique. The extracted frequency bands are categorized across a range of about 30 Hz, as Delta band (δ, 0.5-4 Hz), Theta band (θ, 4-8 Hz), Alpha band (α, 8-13 Hz) and Beta band (β, 13-30 Hz) [39]. When using the power spectrum ratio technique for accessing EEG data, the filtered measurements are then translated to power spectrum density (PSD) via Fast Fourier Transform. An energy spectrum density (ESD) can then be calculated by dividing the PSD area of each band by the respective frequency range of each band [39].

2.5.3 Skin Conductance & Galvanic Skin Response

1) Skin Conductance

More recent research focuses on skin measurements for stress detection as it provides for an easy interface for instrumentation. The skin response primarily focused on is electrodermal activity (EDA), or more commonly known as galvanic skin response (GSR), which measures skin conductance. Skin conductance is the susceptibility of the skin to conduct electricity. This conductivity is based on sweat gland activity which often activates in response to high stress, or fight-or-flight, situations [40]. During increased stress perspiration increases causing resistance to current flow to drop, inversely affecting the conductivity of skin. This relationship is why conductance is used opposed to resistance. Conductance has a directly proportional relationship to increase in perspiration, and furthermore indicative of increased stress. Though GSR has been used to detect stress, it is also worthwhile to note that GSR, like other biomarkers, is a response to arousal, which could be positive

[1] Fp is used to identify forehead placements. Not to be confused with Frontal-Parietal Lobe, which does not exist.

[2] The Central Lobe is used for identification purposes only. [38]

(“elation”) or negative (“fight-or-flight”) [41].

2) Galvanic Skin Response (GSR)

Galvanic skin response relies on the conductivity of skin in response to stimuli. GSR measures a skin conductance level, while monitoring the change in activity. Skin conductance naturally increases over time (especially in humid environments), so transient increases are targeted for electrodermal activity [42]. The natural rise in conductance is called a tonic skin response. This should be noted for reference points, but is generally not used for marking significant activity. Instead phasic responses are targeted. These are the rapid transient peaks that occur due to stimuli such as a stressor. Recorded values are typically in the range of micro Siemens (μS), though often units of resistance (kΩ-MΩ) are referred to both in measurement and in defining a range of sensing [40].

GSR measurements have become a more popular form of stress detection as it generally requires a less cumbersome setup opposed to EEG and ECG setups. GSR measurements are typically taken at the finger, but some research has measured GSR at the wrist with good correlation to finger measurements [43, 44], making wrist measurements a viable alternative to increase wearability. Another convenience factor is that finger and wrist worn GSR electrodes, unlike those of EEG and ECG, do not always require gels for conductively. Although there are systems that recommend them based on the type of electrode used, it is not always necessary, especially if the subject wearing it has moist skin. Dry GSR electrodes can be placed directly to skin while still being able to measure electrodermal activity [43].

2.5.4 Blood Activity & Photoplethysmography

1) Blood Activity

Inherent in the change of heart rate and heart rate variability is a change in blood volume and blood pressure. Blood volume pulse (BVP) is the phasic change in blood volume that corresponds to each heart beat interval [45]. Furthermore, BVP is also used to determine changes in blood pressure in correspondence with blood volume. Variability in blood pressure is due to vasodilation and vasoconstriction of arteries, capillaries and other vasculature which can be discerned by BVP measurements [45]. These fluctuations of blood pressure and blood volume are direct products of heart activity. Therefore, another means of stress measurement is made available by way of blood volume pulse.

2) Photoplethysmography (PPG)

Photoplethysmography (PPG) is a low-cost, non-invasive optical technique that is commonly used to detect blood volume changes in microvasculature [46]. A PPG sensor simply uses an optical pulse generated by a red or near-infrared (NIR) light source (typically an LED), with a closely placed photodetector acting as the receiver of reflected light. The amount of light received back at the photodetector gives insight to the amount of blood volume in the area being illuminated. The less light received by the photodetector means that more light was absorbed at the sight of illumination, which directly corresponds to a higher blood volume [46]. When pulsed at a high enough rate, blood volume pulse (BVP) can be determined with this optical approach. From this, heart rate and heart rate variability can be deduced [47]. Hence, PPG provides a cheaper alternative to ECG measurements. Several studies have been conducted to test the validity of PPG sensor data compared the ECG standard and have shown that PPG sensors provide comparable results [48–51].

2.5.5 Other Physiological Measures of Stress

1) Muscle Activity & EMG

Neural activity leading to involuntary muscle control is another byproduct of SNS activation. Muscle action potentials have been used in studies to identify stress response. A study conducted in 1994 by Lundberg, et al, shows that trapezoid muscle action potentials highly correlate to perceived stress scores and blood pressure response to stress [52]. EMG sensor usage in affective computing has seemed to decline in recent years due to the more popular sensors (i.e. PPG, EDA). Many of the afore mentioned companies offer reliable EMG sensors for sensor fusion (simultaneous sensing) along with the more commonly used sensors. The technology involved in EMG sensing is similar to ECG and EEG in the fact that it uses electrodes to detect potential spikes. However, the source of the targeted potential is from the skeletal muscles which produce a range of less than 50 μV up to 30 mV [53]. An issue with this is that the recordings are extremely localized and quality is dependent on the muscle tone of the individual being tested. Lipid layers covering muscle greatly impede the measurement of EMG signals.

2) Respiratory Response, Piezoelectricity, & Electromagnetic Generation

Respiratory activity has been another physiological feature that has been used to indicate stress. Ventilation has been proven to be a result of the autonomic nervous system in response to mental and physical stress [54]. Hyperventilation in particular has been associated with stress. In the process of hyperventilation more CO_2 leaves the body than can be produced by metabolic processes, which may result in a host of physiological consequences. These include reductions in cerebral and myocardial perfusion and O_2 delivery, ECG and EEG changes, withdrawal of cardiac vagal tone, muscle spasms and tetanus [54, 55]. Since the changes that occur due to respiratory changes can be sensed from other sources directly (ECG and EEG), those sources are more likely used. A study by Jennifer Healey and Rosalind Picard show that heart activity and skin conductance show greater correlation to stress than both respiration and EMG [34]. However, the technology involved is usually in the form of a piezoelectric transducer which changes linearly in response to longitudinal pull. Piezoelectric transducers are ceramic material that provide electrical response to physical changes. This transducer is often placed on a belt and clipped on to an individual around their chest so that the transducer provides respective output as their chest expands and contracts. Alternatively, electromagnetics can be used in place of the piezo material. A study by Bryson Padasdao and Olga Boric-Lubecke exhibit a way to use a servo motor in place of the piezo transducer [56].

2.6 Physical Stress-Based Affective Computing [87]

The following will discuss the physical manifestations of stress, which include facial features and behavioral traits of individuals experiencing stress. These modes of measurement utilize automated facial expression analysis software and body tracking to identify affective states.

2.6.1 Facial Features

1) Facial Expression Analysis

Documentation dating back to the late 1800s, such as Charles Darwin's book *The Expression of the Emotions in Man and Animals*, correlate facial expression to emotional state. Studies in the late 1900s and early 2000s have confirmed this connection of facial expression to specific emotional states via the study of the hypothlamic-pituitary-adrenocortical

(HPA) axis and cardiovascular responses to stress [57]. A more recent study conducted by J. S. Lerner et al. has identified a positive association of fear with cardiovascular and cortisol stress response, whereas a negative association of these responses was identified for indignation (anger and disgust) [57]. This same study also showed that the facial expression analysis correlated with biological markers of stress better than self-reported emotional states.

A rising mode of affective computing is in the advancement of automated facial expression analysis (AFEA) algorithms. Facial expression analysis is a technique that many people have used organically to detect when someone is feeling sad, upset, happy, etc. It has also played an essential role in detecting deceit [58]. Many facial expression recognition systems are based on a protocol called FACS (Facial Action Code System) published by Paul Ekman and Wallace Friesen in 1978, later updated in 1992, and then again in 2002 [59, 60]. This system objectively measures the frequency and intensity of facial expressions and deduces what is referred to as an action unit (AU). Action units are the smallest discriminable movements detectable in a facial expression [59]. FACS is separate from emotion in nature, yet its AUs are significantly appreciated in detecting emotional state based on facial expression. AUs dealing with eye constriction, lip, cheek and brow arrangement are essential in facial expression recognition software for computing affective state.

This "rule-based" coding approach of FACS is employed as a part of the analytical class of automated face recognition. There are in fact two major classes of automated face recognition: analytical and holistic. The difference between the two classes is in the template references. The analytical class focuses on geometrical feature extraction, while the holistic class focuses on usage of a feature vector to represent an entire facial template [61]. Facial expression recognition systems such as FACS have enabled the possibility for automated facial expression analysis. Lien et al. have demonstrated an AFEA system based on FACS with up to 93% accuracy [62]. Other commonly used methods for facial expression recognition include Hidden Markov Models (HMMs), contour models, principle component analysis (PCA), and artificial neural networks (ANNs) [62, 63].

Leaders in affective computing include Affectiva, Inc. and Emotient, Inc. Affectiva, like Empatica, Inc., was formed out of MIT's Media Lab and co-founded by Professor, and founder/director of the Affective Computing Research Group, Rosalind Picard [64]. Affectiva produces a FACS-based AFEA called Affdex, which employs advanced computer vision and machine learning within a scalable cloud based structure to perform facial analysis given any standard webcam [65]. The system intends to extend beyond the basic emotions (anger, joy, surprise, disgust, sadness, and fear) to provide better real-world assessment of multimedia [65]. Though the forefront goal of the Affdex software is to assess user response to commercial content, the core of the system assesses user emotion and has great potential for other applications such as the assessment of pain, depression, and helping individuals in the autism spectrum [66].

Emotient, Inc. is an AFEA company that has produced software for commercial applications, now under the authority of Apple due to an early 2016 acquisition. The company started out of the University of California, San Diego (UCSD) where the original platform Computer Expression Recognition Toolbox (CERT) was created. The group who innovated the FACS based system later converted the AFEA platform into Emotient in 2012 and commercially offered the software under the name FACET (FACial Expression Toolkit). The FACET software has been evaluated in research against a Speech-based Emotion Recognition system for analyzing job interview videos [67]. It has also been assessed in applications of automated detection of driver fatigue and automated teaching systems [68]. These are only a few of the applications. Many more application have been speculated within the medical, educational, safety, and security fields.

2) Eye Tracking

Eye activity, specifically pupil dilation and blink rate, has been used in some stress studies to correlate with physiological measures under stress [69, 70]. The study done by Haak et al. shows a strong relationship between eye blink frequency and emotional stress via correlation with EEG measurements. This study used driving simulations to assess blink rate under stress and non-stress conditions. The study shows that eye blink frequency tends to increase positively with stress [70]. Pupil dilation has proved to be quite useful in increasing confidence of stress detection. A study conducted by Barreto et al. shows that inclusion of pupil dilation in the analysis of stress increases accuracy of detection [69]. This assessment of pupil dilation was based on a study from Partala & Surakka in 2002 which shows a distinct pattern of eye dilation associated with emotional arousal [71].

Alternative to total face assessment, studies have also isolated eye activity for evaluation in affective computing [72, 73]. When looking at eye activity alone there are a multitude of eye tracker systems that can fit the need of extracting important information regarding eye placement and movement. Two systems in particular are the Tobii X120 series and The Eye Tribe ET1000 eye trackers. The Tobii X120 has been used in affective computing research for assessing emotional state during visual stimuli among a normal population (via video) [80], as well as among an Autistic population (via virtual reality environment) [74]. Both studies have shown the Tobii X120 to be effective in tracking and extracting valuable eye activity. The Tobii X120 has since been replaced by the Tobii Pro X3-120, which has the same performance in a smaller form factor.

2.6.2 Behavior & Gesturing

Due to the physical and physiological manifestations of stress in an individual, there is also a behavioral component that accompanies these symptoms. This could include fist or jaw clenching, body stiffness, crossing of arms, pacing, jittering, and a number of other behavior [75, 76]. Behavior and gesture analysis has been employed for studies regarding those in the Autism spectrum [77]. Visual sensors like those used for facial features can be used for discerning stress behavior via posture and movement sensing. The study carried out by Piana et al. utilizes an Xbox Kinect to capture gesture features for analysis of the emotional state in Autistic children [77]. Automated gesture analysis systems utilize the same visual processing algorithms as used in AFEA and eye tracker systems (HMM, ANNs, PCA, etc.) [61]. Hence, a similar system could potentially be used for aiding in stress detection of non-Autistic individuals.

2.7 Selected Measures of Stress & Instrumentation

Due to the cost efficiency, easy of instrumentation, non-invasive nature, and reliability of their corresponding sensors, the following measures of stress were chosen for this thesis: GSR, facial expression, and heart rate. A two-electrode system for GSR measurements was used. The specific device used was the Shimmer GSR+ which was developed by Shimmer Sensing [78]. It is a Bluetooth enabled device that houses EDA and PPG sensors capable of measuring GSR and heart rate simultaneously. Hence, the same device was used to collect heart rate information. For measurements, this module is to be strapped around the wrist, with the GSR electrodes placed either at the proximal phalanx (base) or intermediate phalanx (middle section) of the middle and ring fingers. The PPG sensor is then strapped at the distal phalanx (fingertip) of the index finger. These placements are to be set on the non-dominant hand of the respondent (person undergoing measurements), in which there should be minimum movement to ensure the best quality signals for measurement. As for the facial expression analysis, a software package (FACET) provided by Emotient was used to detect distinct emotional valence. In addition to the FACET software, this instrumentation requires only a camera and significant lighting. Both the Emotient FACET software and the Shimmer GSR+ module were integrated with the iMotions platform to provide for a common conduit to feed into the framework presented in this thesis. Within the iMotions platform stimuli can be queued to invoke psychological reaction by a respondent, while also measuring their physical and physiological response.

Chapter 3

Developing an IoT Infrastructure for Fall Detection [86]

This chapter discusses the details of a proposed IoT infrastructure for voice activated fall detection. The system layout, its components, and their function will be explored as well. A large emphasis is placed on the voice interaction model for the system, in which its operation is discussed in full detail.

3.1 IoT Infrastructure

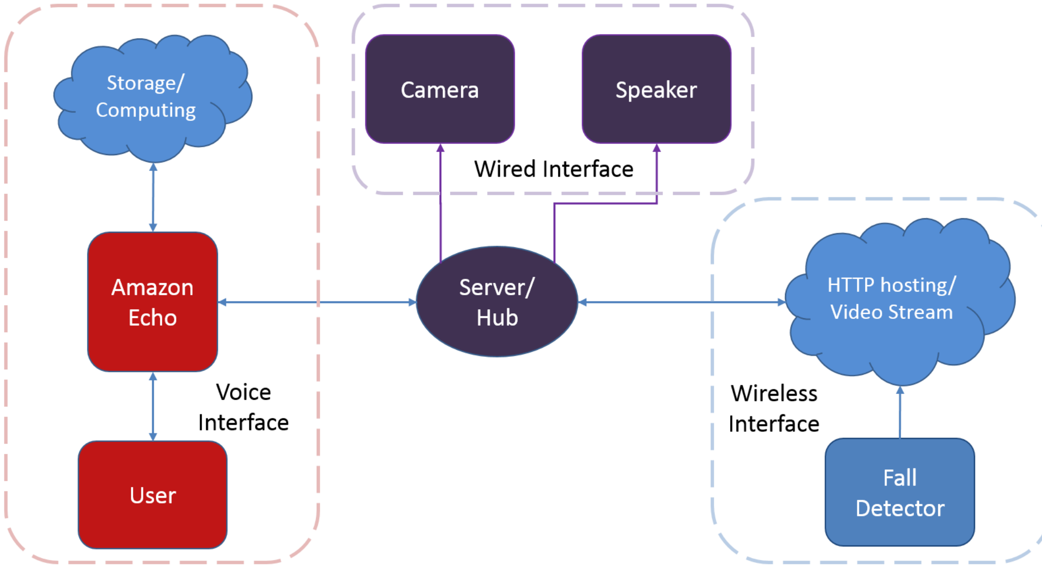

Figure 3.1: System diagram for IoT-based fall detection. Blocks in red represent components of the system's voice interface. Blocks in purple represent all components physically connected to the server/hub. Blue shapes represent wireless components of system. Blue arrows represent two-way communication, while purple arrows represent one-way communication.

The goal of this system is to integrate fall detection into a smart home environment in efforts to create a more robust intervention and safety model to aid older adults. This system would work primarily from a local Wi-Fi network. Like most IoT systems this system is designed with a central hub for communication that will perform data processing, decision making, and relay of messages. This central hub will act as an intermediary between all components of the system. The components of the system include the following (See *Figure 3.1* for the layout of the system components):

- ▷ HTTP Server/hub
- ▷ Fall detection device
- ▷ Amazon Echo/Alexa
- ▷ Speaker
- ▷ Webcam

A Raspberry Pi Model B+ is being used as the central hub of the system, which hosts an HTTP server that communicates with all the wireless components of the system. The peripheral components of the system comprise of a Tiva C Launchpad equipped with a Wi-Fi expansion board and an accelerometer to act as the fall detection device, a wired speaker, an Amazon Echo accessing the Alexa Voice Services (AVS) to act as the voice processing unit, and a Logitech c920 webcam. The Tiva C Launchpad houses the fall detection algorithm for the system and communicates a detected fall to the central hub via HTTP request. Upon this detection, the hub acts appropriately to launch the interaction model via text-to-speech broadcasted through a wired speaker. This interaction model is later detailed in the section *System Interaction Model*. The Amazon Echo is capable of voice recognition and determining actions based on verbal input by accessing Alexa, Amazons cloud based voice services. The added value of the Amazon Echo and AVS is two-fold: (1) it adds a level of convenience in the sense that the user does not have to press anything, and (2) it allows for further confirmation of a detected fall. To the point of the first benefit, the use of the user's voice provides a natural interface to the home assistance system. It bypasses the need for pressing buttons or touch anything at all. To the point of the second benefit, it aids in the overall efficiency of the fall detection algorithm as it allows the user to confirm an actual fall prior to advancing to help options. This can potentially further reduce the false positive rate of the system when considering the launch of intervention.

3.2 Fall Detection

The goal of this infrastructure is to provide a proof of concept for an IoT integrated fall detector within a smart home environment. By developing an internet connected device capable of detecting falls, a smart home is enabled to become a critical part of home aid assistance. Due to the statistics on fall-related deaths and other health decline [1, 2, 6], enabling a smart home with an IoT fall detector can be revolutionary in terms of the longevity of older adults living at home. The main objective is to add a layer of safety to a home environment that allows the older adult to live more independently, while also easing the concerns of caregivers and loved ones when they are away.

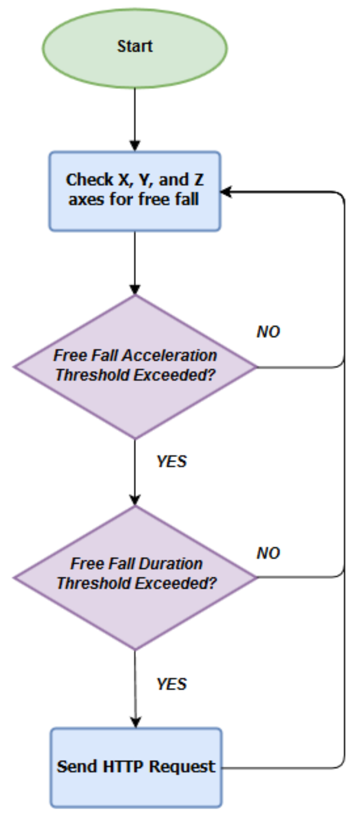

Figure 3.2: Simple algorithm for fall detection

In strides to develop such a device, a common development board, the Tiva C Launchpad, was used as the starting platform. Via an extension board, an accelerometer has been attached to the Tiva C Launchpad to perform acceleration measurements. These acceleration measurements sense the motion and speed of the device. The ADXL345 3-axis accelerometer was used for this purpose.

For the device to work properly as a fall detector, the device must implement an algorithm that can detect a fall. The fall detection algorithm in our work is based on the algorithm proposed in [79]. The algorithm works via the use of threshold based interrupts. Two thresholds are set for free fall: an acceleration threshold and a free fall duration threshold. When an acceleration greater than the threshold is reached for a time longer than that of the free fall duration, an interrupt is generated. The interrupt service routine then sends an HTTP request to the central hub of the IoT system. This is illustrated in *Figure 3.2*. The fall detection algorithm initiates the interaction model discussed in the following section *System Interaction Model*.

3.3 System Interaction Model

One large hurdle with fall detection algorithms is the balance between specificity and sensitivity. Specificity is the measure of how many true negatives are avoided by the system, while sensitivity is the measure of true positives detected. An ideal system would have very high specificity and sensitivity. However, naturally, high sensitivity brings about false positives, which further brings about an annoyance to the system's users. Though our system is not specifically geared toward producing the most efficient fall detector, it will add a layer of confirmation to reduce false positives. This layer of confirmation is supported by the Amazon Echo through an interaction model. Amazon Echo helps to guide the course of action to be taken once the fall detector has alerted that a fall event has taken place.

The current interaction model in place responds verbally to detected falls. The system uses an Amazon Echo as its central voice processor. Amazon echo responds to the detected fall by asking the wearer of the fall detection device if they have fallen. Upon this posed question, there are provisions made for three possible responses:

1. Positive response (confirmation of fall)
2. Negative response (decline of fall)
3. No response

These responses are detailed below and illustrated in *Fig. 3.3*.

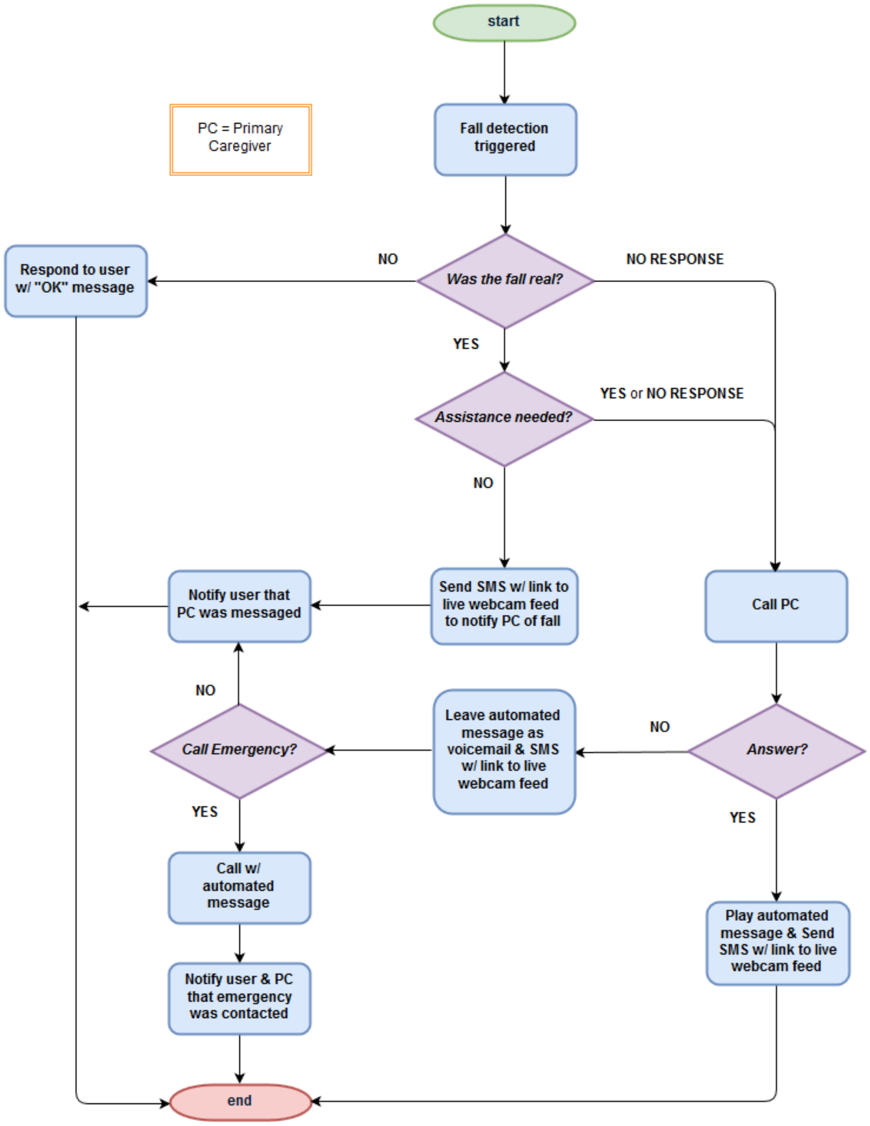

Figure 3.3: System Interaction Model

3.3.1 Positive Response

If the user verbally confirms the fall, the system then asks if they would like to call for assistance. If that question is then answered positively, then the primary caregiver on record is contacted with an automated message that alerts them regarding the fall. Along with this verbal message, a SMS text message will be delivered for the primary caregiver to review. If the primary caregiver is not available (i.e. call is missed) then a SMS text message and voicemail message are left on the primary caregiver's phone. The SMS text message will contain a link to a live video feed of the user so that the primary caregiver can visually identify their state and provide more information on what next step to take (i.e. call to check in on the user or call for an ambulance in the case of emergency). Following a missed call and the sending of these messages, the system will also ask the user if they would like to contact 911 directly. If a positive response is given, then an automated distress message with the user's information (full name, address, and phone number) would be relayed to 911. Once this occurs, another SMS text message is sent to the primary caregiver to let them know that 911 was contacted. The user is also notified verbally that help has been contacted. For lab testing, 911 has not actually been called to avoid unwarranted calls to emergency call centers. Instead, a phone number of a secondary caregiver was used.

3.3.2 Negative Response

If the user denies the fall then a verbal message is communicated to the user to confirm acknowledgment of the response and no further action is taken. However, if the user confirms the fall, but declines the need for help, then an SMS text message is sent to the primary caregiver to relay that a fall was detected and confirmed. This message also contains a link to the live video feed of the user for monitoring of their condition. Finally, the system responds verbally to the user to make them aware that it acknowledged their response and that a message has been sent to the primary caregiver. It's important to note here that despite a negative response to needing help after a fall, the primary caregiver is still notified of the incident. Although one in three older adults 65 and older fall each year, less than half actually report the incident to their doctor [2]. So, this feature gives the caregiver the opportunity to report the incident on the behalf of the user. Such a provision could potentially afford the older person the opportunity to receive proper care in a timely fashion despite their initial assessment of the fall.

3.3.3 No Response

If no response is detected, then this scenario is treated as an emergency condition (i.e. user is unconscious or conscious but unable to speak). This bypasses the decision blocks for responses and directly contacts the primary caregiver. As an act of precaution to reduce unnecessary calls to local authorities regarding the incident, the call to 911 is omitted and the decision of action to take is left to the primary caregiver. The interaction model is designed with convenience in mind, since it shouldn't be expected for older adults to know how to setup or operate complicated software/hardware for the system. The interface is primarily audio based. However, in the case of the user being conscious but unable to speak (or speak loud enough), it is optional to have a button input that can provide the same confirmation of yes or no.

Chapter 4

Developing a Framework for Stress Detection

A goal of this research was to create a framework that could be used to pave way toward a non-invasive method of determining psychological stress. The proposed framework can be used to collect and pre-process physiological data for the purpose of validating galvanic skin response (GSR), heart rate (HR), and emotional valence (EV) measurements against the cortisol and self-reporting benchmarks for stress detection. The framework allows for real-time processing of GSR, the measurement of skin conductance, and EV, the overall emotional state (positive, negative, or neutral), while also saving data for post-processing. Furthermore, the framework can be used to enhance the TSST protocol via automation and IoT connectivity.

4.1 Stress Detection Framework

The proposed stress detection framework consists of four distinct phases:

- ▷ Phase I: Raw data collection from sensors
- ▷ Phase II: Parameter setting for GSR peak detection, and data routing
- ▷ Phase III: GSR peak detection, emotional valence detection for facial expression, and storage for post-processing
- ▷ Phase IV: Stress Recognition, Data Reporting and Visualization

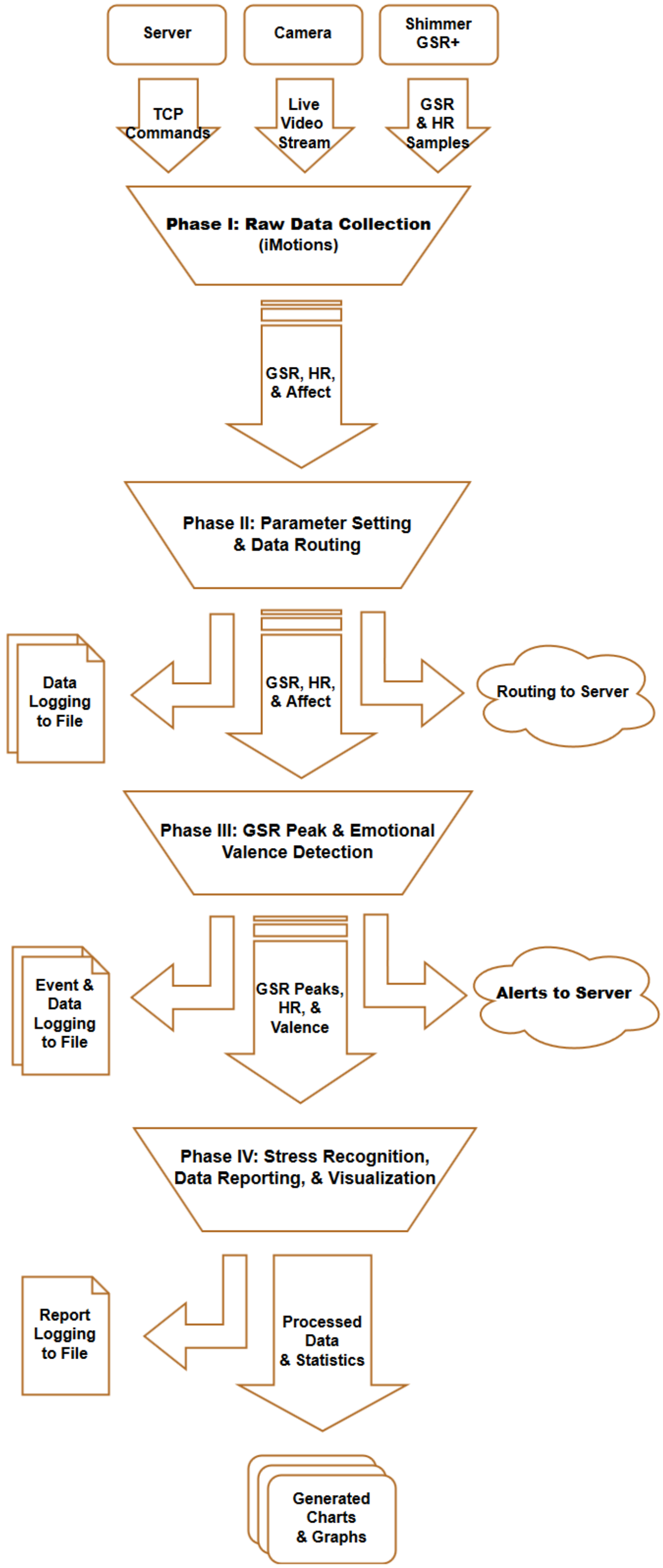

Figure 4.1: Stress Detection Framework (all phases). Each phase has its own inputs and outputs.

4.1.1 Phase I: Raw Data Collection from Sensors

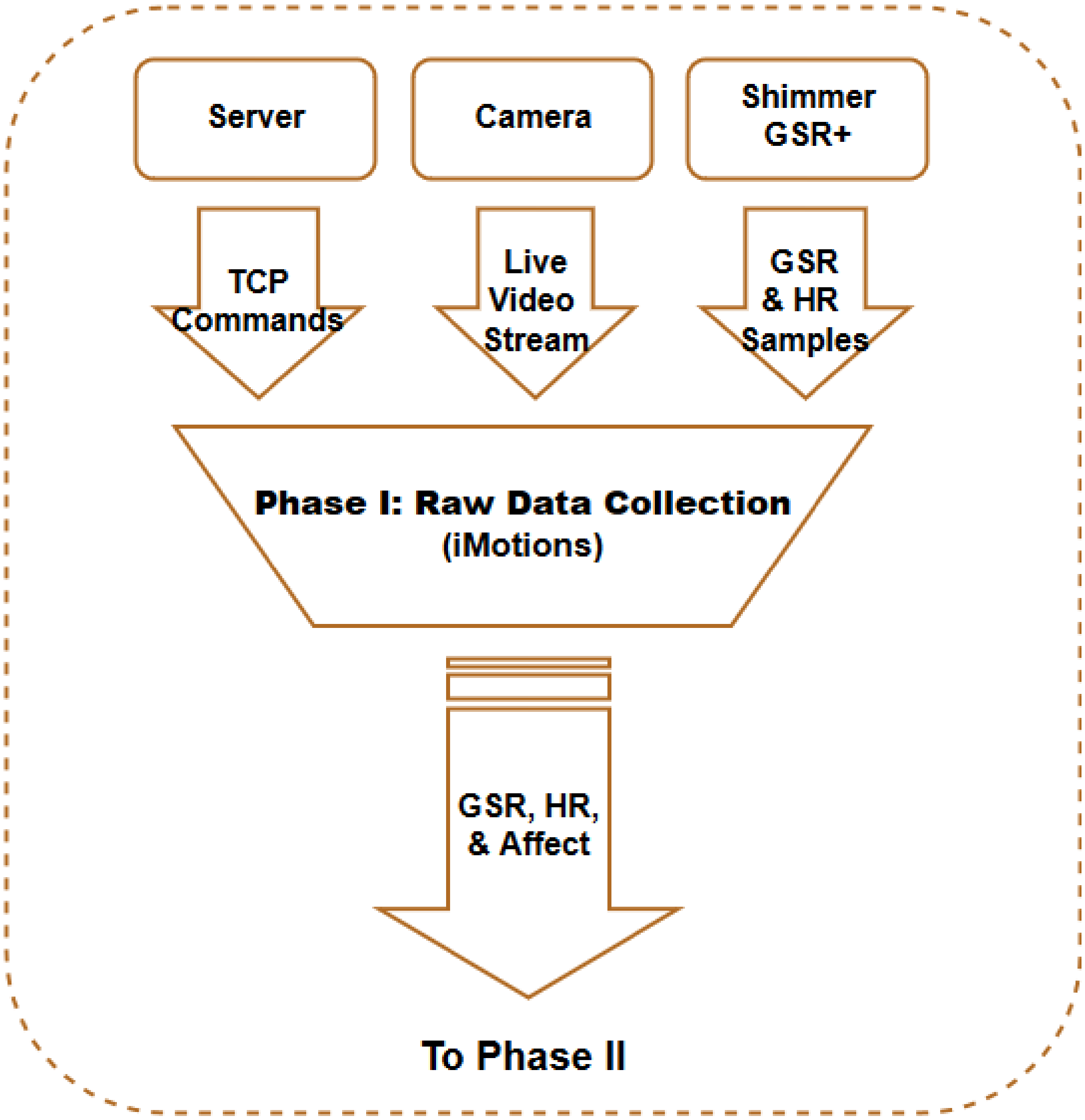

Figure 4.2: Phase I of Stress Detection Framework. Raw GSR, HR, and video data are collected from sensors. GSR, HR and affect data are then forwarded to Phase II.

Initial data collection is handled by a biosensor platform called iMotions [80], which allows for data from multiple biosensors to be collected simultaneously. The platform has its own analysis software for processing biosensor data like GSR, PPG, and facial expressions. Though this platform contains many features for data collection and analysis, the platform is not suited to address stress specifically; nor does it provide real-time analysis of critical features chosen for this research, namely GSR peak detection and valence thresholding. Hence, the framework designed for this thesis presents a means for real-time GSR peak detection and valence thresholding, as well as post-processed sensor fusion, directed for psychological stress.

The Shimmer GSR+ device provides GSR and heart rate data wirelessly to iMotions to be rerouted and processed later. Similarly, live video feed producing emotion and valence data is collected and rerouted to Phase II. All data collected in Phase I is funneled to Phase II for parameter setting and data routing.

4.1.2 Phase II: Parameter Setting for GSR Peak Detection, and Data Routing

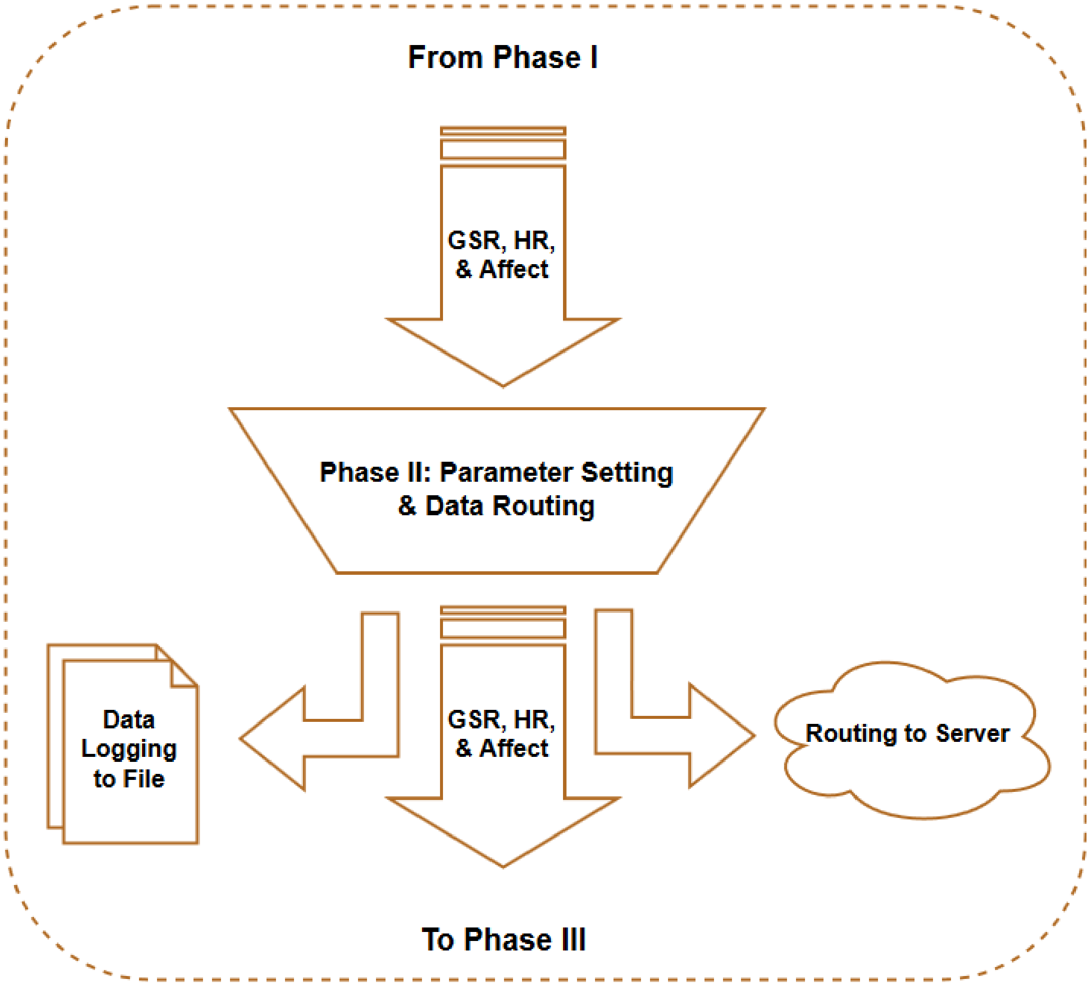

Figure 4.3: Phase II of Stress Detection Framework. GSR, HR, and affect data are routed from Phase I to Phase III. Optionally, data can be rerouted to a server or file for later processing.

Phase II of the framework has two main functions: (1) setting up parameters for data processing and (2) data routing. The setup parameters are primarily for defining how GSR data will be processed, but also sets up routing and logging options for the framework. GSR parameters include critical features for GSR peak detection, such as data window sizing and amplitude thresholds. These parameters will be more thoroughly discussed in Section 4.2 (GSR Data Processing). As far as routing, this phase provides three forms of redirection: (1) to dump file in unprocessed format, (2) to a local server in unprocessed format, and (3) to Phase III for data processing.

The first option for redirection is merely for test purposes. It allows for data to be captured and saved for later processing. This is useful for offline situations such as when no internet connect is available and data has to be collected until a connection is available again. This is also useful for testing data sets using different algorithms during the data processing phase. Data processing can be set up in a modular fashion, so as to perform different algorithms on the same set of data for comparison in performance. So, appropriately, this phase can be configured to either accept data from a live stream or from a dumped file previously streamed and captured. The second option for redirection of data is to provide an outlet for cloud computing if ever warranted. This rerouting option allows for off-board processing in which Phase III can take place either by a remote version of the original framework design or by a third-party software entirely. Currently, these possibilities are not being leveraged. Yet, the feature is provided for future adaptation if ever warranted.

While the first two forms of data rerouting are optional features, the third is essential to the core of the frameworks design. Phase II is responsible for initializing Phase III and starting it as a separate process with a queue structure for communicating data back and forth. When data is routed directly to Phase III, it is first slightly pre-processed by dynamically dividing the data stream into discrete lines of sensor data. As this is being done, each discrete line of data is placed on the queue for pipelining to the data processing phase. This process of data reception, slight-parsing, and pushing to Phase III is continued until either all data is collected or operation of the framework is manually terminated.

4.1.3 Phase III: GSR Peak Detection, Emotional Valence Detection for Facial Expression, and Storage for Post-processing

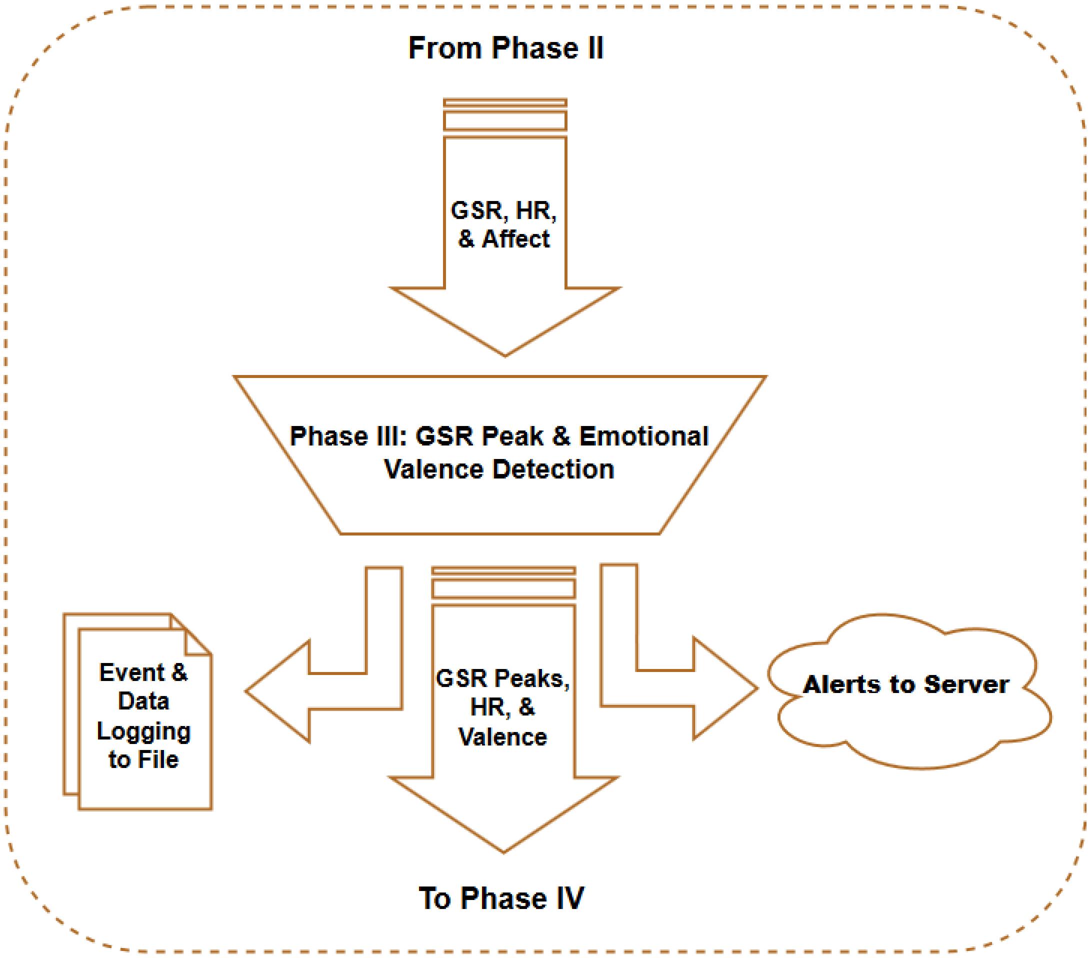

Figure 4.4: Phase III of Stress Detection Framework. GSR, HR, and affect data from Phase II are processed then forwarded to Phase IV. Events are logged and alerts are sent to server.

Phase III is the data processing core of the framework. For the scope of this thesis, Phase III incorporates the following functionality: time and data extraction (data parsing and timestamp tracking), GSR processing (peak detection, and binarization), emotional valence processing (thresholding and binarization), heart rate tracking, and event logging.

After data on the queue passes from Phase II the discrete lines of data are parsed to extract time and sensor data from the stream prior to individual data processing. Timestamps are appended to each set of data for accurate processing in the time domain. A parsed line of data can contain GSR and heart rate data (together), emotion and valence data, or metadata for the incoming sensor data. Based on the contents of the parsed data, data is processed accordingly. For parsed data containing GSR and heart rate both timestamped data samples are added to a stream to be dumped to a file for logging. Additionally, the incoming GSR data is added to a buffering window for peak detection. Once the buffering window meets the parameterized size specified in Phase II, peak detection algorithm is applied to the window of data. This process continues upon receipt of each GSR data, discarding the oldest data point and effectively forming a moving window of data. The actual algorithm applied for peak detection will be examined more closely in a designated section (GSR Data Processing) later. Then, once GSR data run through peak detection. Parsed data containing emotion and valence data is further reduced to valence only and a threshold is applied. This will be further examined later as well. Data streams containing metadata will be used for data logging and reporting in Phases III and IV, respectively.

Additional to the data processing taking place in Phase III, channels of communication are maintained for passing of data. This is done in three ways: (1) logging to file for reporting and post-processing, (2) communication to a local server for detected GSR peaks, (3) transport of processed data to Phase IV. Regarding the first channel of communication, parsed data streams logged to file are used for representing stress during post-processing. Also, metadata passed from Phases I and II are combined with processed data to form real-time event logging based on the introduction of new stimuli to the framework, as well as any GSR peaks found during data processing. Along with this event logging, this phase of the framework posts GSR peak events as a HTTP requests to a local server, which forms the second channel of communication. This allows for real-time response to GSR peaks, which signify peaks of arousal. These events communicated to a server can be further propagated to activate other features within the connected IoT network. This could include actions such as sending a SMS message, making a phone call, or launching some sort of intervention, like music or video. This outlet allows for further expansion of the framework into a more encompassing solution to stress management. Lastly, processed data is placed onto a queue for reporting and plotting in Phase IV. This reporting and plotting will be detailed in the following section.

4.1.4 Phase IV: Stress Recognition, Data Reporting and Visualization

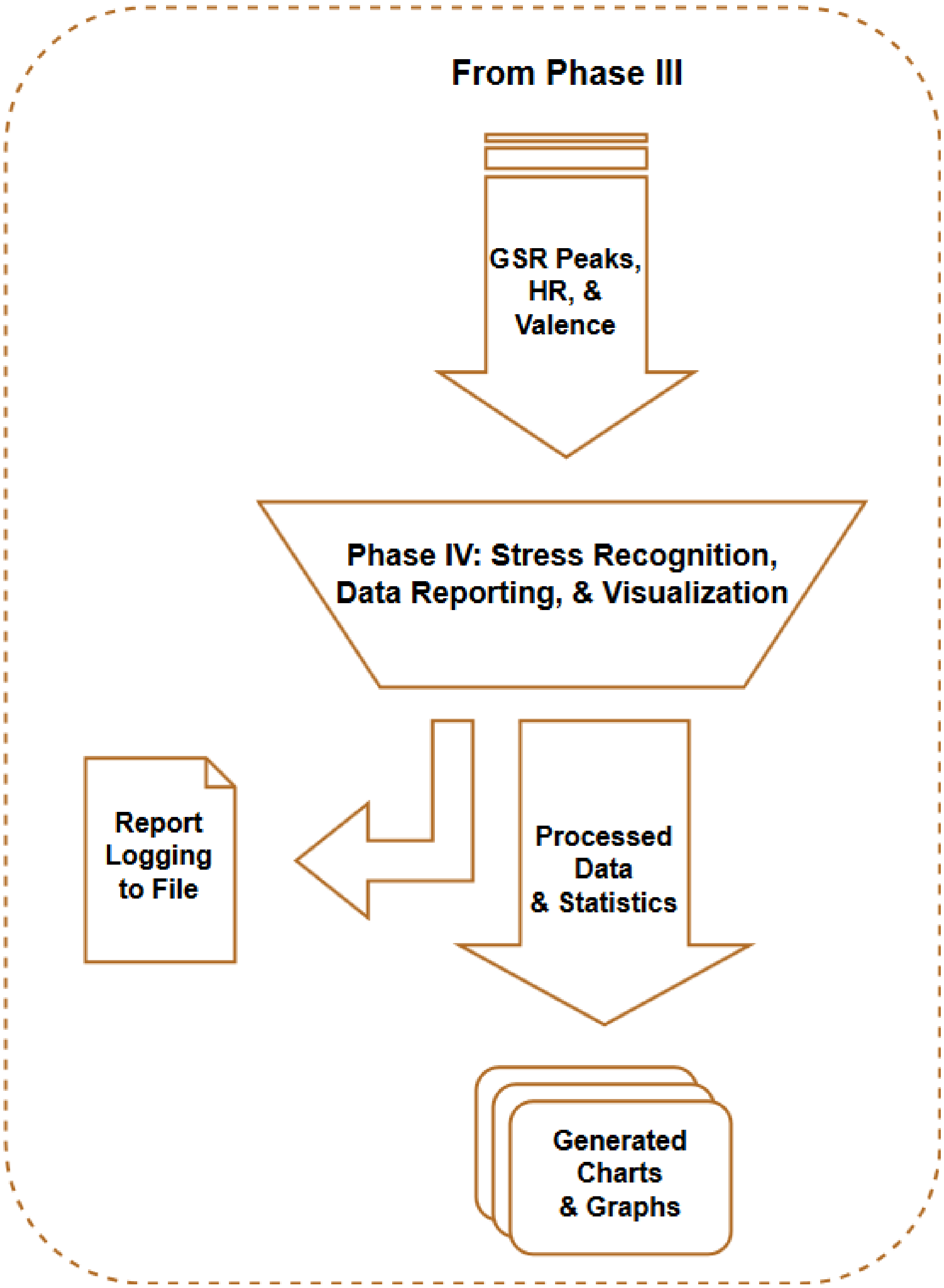

Figure 4.5: Phase IV of Stress Detection Framework. Processed data is reported in a log and graphs are generated for visualization.

After the real-time data has been processed and logged, Phase IV is tasked with further processing the data to better represent stress according to the sensor output. One of the post-processing tasks is binarization of GSR data, which is done quantify both the frequency and ranges of time in which GSR peaks were found. Also, binarization is quite useful when analyzing an aggregate of individuals exposed to the same stimuli for statistical purposes. This binarization and aggregation processes will be further detailed in the following section, *GSR Processing*. Another form of post-processing taking place within this phase is an application of binarized valence data to be used along with the binarized GSR peaks for representing psychological stress. Modules are also put in place to perform calculations for representing psychological stress based on heart rate as well. Potential approaches to representing psychological stress using binary thresholding will be explored further in section *Quantifying Stress Via Sensor Fusion*. In regards to data reporting, statistical data produced in post processing is appended to the event log started during Phase III. The final function of Phase IV is to generate visual plots of processed data, which illustrate heart rate, GSR peaks, and statistics formed from any applied representation of psychological stress. These data sets are automated to plot immediately once all data has been received and processed, allowing an examiner to graphically view the respondents response to the presented stimuli.

4.2 GSR Data Processing

In processing GSR data there are three main operations taking place: (1) peak detection, (2) binarization, and (3) aggregation of binarized peaks. While only peak detection is done in real-time, the remaining two are performed in post-processing. Binarization and aggregation of binarized peaks can be used for statistical modelling of psychological stress in response to stimuli across a population of respondents. Each GSR operation and their significance will be detailed in the following sections.

4.2.1 Peak Detection

The critical feature of galvanic skin response is its electrical response to sympathetic nervous system (SNS) activity. The SNS is responsible for facilitating immediate motor action, which is readily sensed at the skins surface [80]. Hence, measuring drastic spikes in skin conductance allows for some insight into what the body is currently experiencing. These drastic spikes form peaks in measured skin conductance, which correspond to psychological arousal. Psychological arousal in its nature can be either good or bad, representing anxiety due to excitement or fright, pleasure or stress. Thus, it is an aim of this research to extract these spike events as identifiers of arousal for later cross-validation and regression against other representations of stress.

GSR signals are composed of two main conductance levels: tonic level and phasic response. A tonic skin conductance level is the slow response due to environmental changes such as temperature and humidity. Because of these environmental changes, overall skin conductance is always changing, however, at a slow rate. Phasic skin response, on the other hand, is a direct product of SNS response so it will exhibit very quick responses. This phasic skin conductance level superimposes the tonic level and forms the level of interest for peak detection. So, in order to analyze the phasic response, while also disregarding the tonic level, a series of computations must occur. First, the tonic level must be removed from the data. This is done by collecting a window of data (which is typically 4 to 8 seconds worth of samples) then computing the median of the data set and removing the median from the center point to reveal the phasic response. This process is done as a moving window to produce phasic data from the center of the window upon receipt of each new GSR data point. This means that phasic data has a lag in response of half the window size.

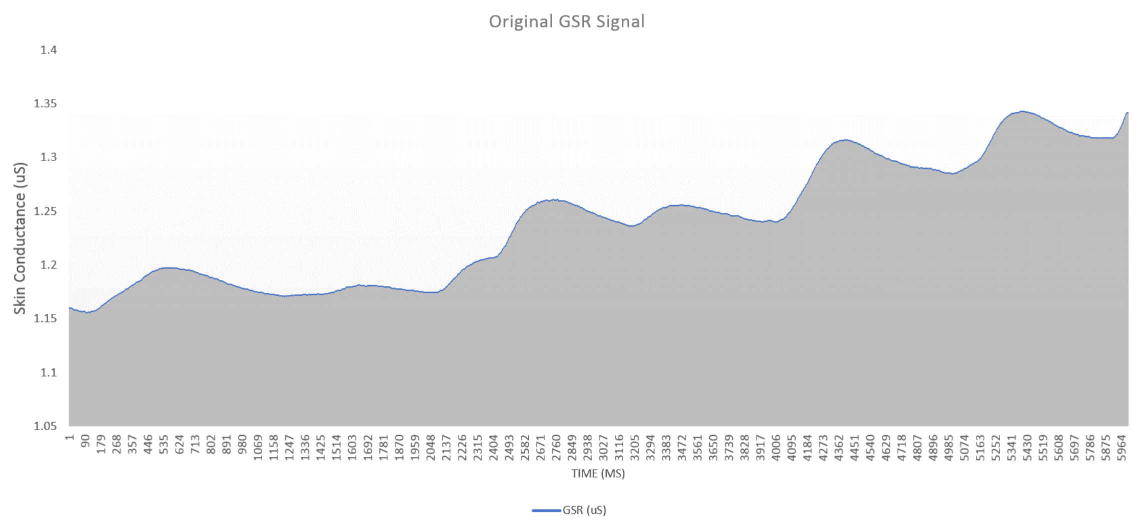

Figure 4.6: Sample GSR Data. Plotted GSR data was originally collected in iMotions (2016). [80]

Once a phasic level is established, peak detection begins by searching for a series of thresholds. The first threshold is an onset threshold, which is the minimum detection level for a rising peak. If the onset threshold is crossed, a second threshold for the peak offset is then searched. Upon finding the peak offset threshold, the peak value is obtained by finding the maximum value between the onset and offset thresholds. Additionally, during the search for a peak onsets and offsets, there is a maximum threshold for jumps between samples. This is a safe guard which helps to remove noise in GSR data by ensuring that the difference between two discrete samples isnt too large. Then, the final step for qualifying the GSR peak is comparing the maximum phasic value found with a minimum peak threshold. Each of these thresholds can be specified as parameters in Phase II of the framework.

Figure 4.7 illustrates phasic data undergoing peak detection given the following parameters: peak onset = 0.01 uS, peak offset = 0 uS, minimum peak threshold (min) = 0.005 uS, jump threshold = 0.01 uS, window size = 8 secs.

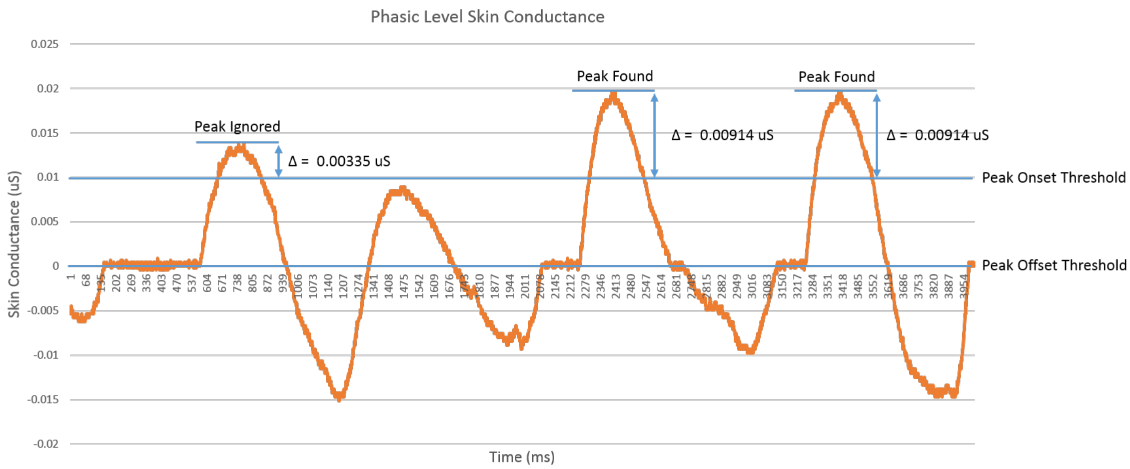

Figure 4.7: Phasic data showing GSR peaks. Original GSR data was originally collected in iMotions (2016) [80]. Phasic data was analyzed by custom software designed for this framework.

4.2.2 Binarization & Aggregation

As the first procedure in post-processing of GSR peaks, the GSR data goes through a binarization process. This process applies an overlapping window of a parameterized length to the data in order to identify ranges of time in which peaks were found. Binarization of data comes into effect in the manner of presence versus absence of any peaks within a given window frame of time. Presence of any peaks are assigned a value of '1', while any frame of data without any detected peaks is assigned '0'. Hence, a binarized window containing 3 peaks would produce the same output as one containing only a single peak, essentially hiding the fact that there were multiple peaks found during that time frame. However, if the window is set small enough, this binarization can be used to quantify the number of discrete GSR peaks found in the data set. Additionally, the overlapping of windows allows for smoothing of data in the sense that a peak found at a border of window frames will be registered as binarized peaks for both windows. This data, once binarized in Phase III, is then interpreted graphically in Phase IV.

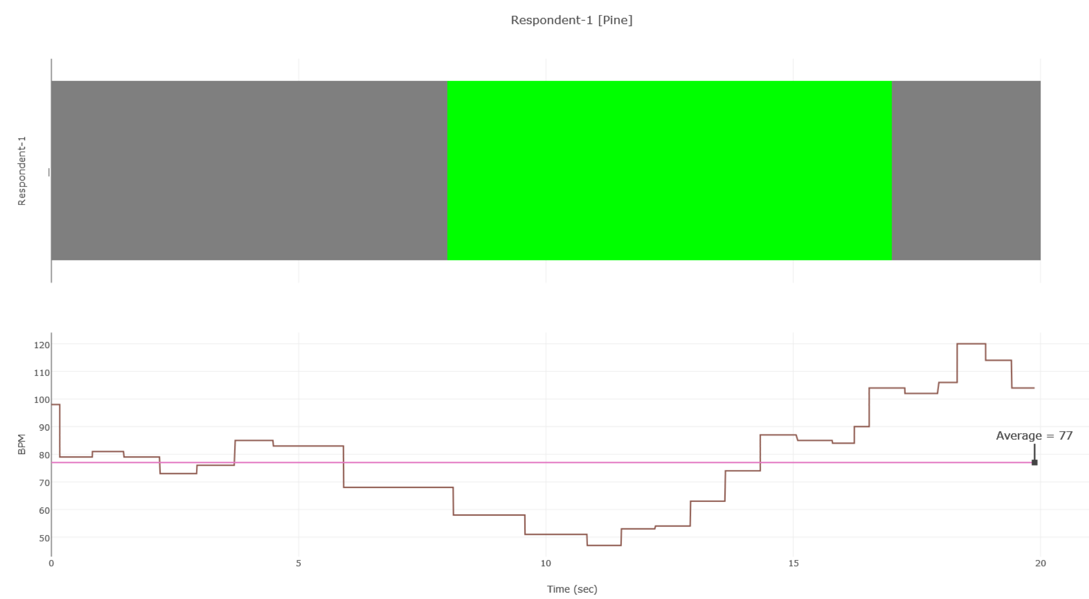

Figure 4.8: Illustration of a binarized GSR peak output, with corresponding measured heart rat. Green denotes presence of GSR peak, while grey represents its absence. Original sensor data was collected in iMotions (2016) [80]. Processing and produced output was performed by the stress framework presented in this thesis.

For statistics on GSR peaks per population, these binarized peaks can be combined across respondents undergoing the same stimuli to make assumptions about a larger population undergoing the same stimuli. For the scope of this thesis, aggregation is merely used for illustrating how many respondents experienced GSR peaks during a given window of time. Aggregated GSR peaks are represented by demographic groups (i.e. age range and sex), which is apparent in *Figure 4.9*. This data is entirely computed in Phase IV, as it is hinged upon having a complete set of GSR peak data from all respondents of interest undergoing a particular stimuli.

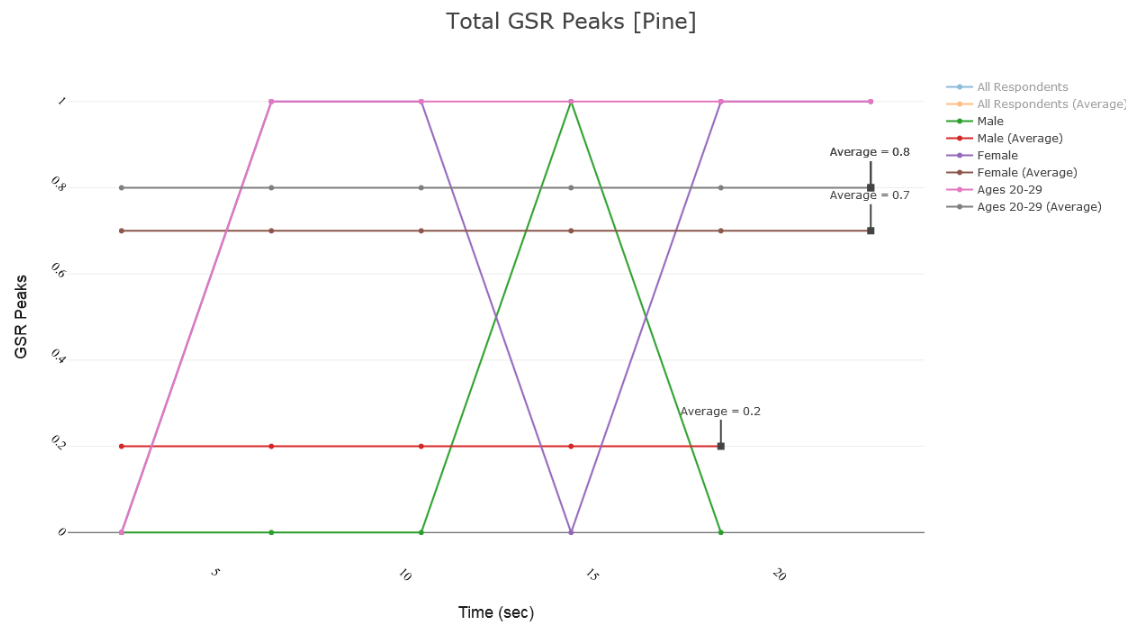

Figure 4.9: Illustration of GSR Peak statistics generated in Phase IV of the Stress Framework. Sample data used for plotting was originally provided by iMotions (2016) [80].

4.3 Automated Facial Expression Analysis

Facial Expression Analysis performed in this thesis is primarily provided by means of Emotients AFEA software which is available as a plug-in for iMotions platform. This software uses a validated set of microexpressions called FACS (Facial Action Code System) to discern different emotions based on facial expression presented in a live video. The software produces confidence levels for each basic emotion (joy, anger, surprise, disgust, sadness, fear), as well as overall emotional valence (positive, negative, neutral), based on the FACS. For the scope of this thesis, only overall valences were extracted from the software. Though there is software to provide confidence levels on emotion, the software does not inherently give any information about psychologically stress. Hence, the framework designed here aims to utilize the emotion information for the specific purpose of identifying facial expressions related to stress. Because GSR peaks represent arousal of any kind, positive or negative, valence information is also extracted to help correlate negative arousal with negative emotion. This combination represents a relatable understanding of psychological stress. So, in order to help discern which valence is dominant, the confidence levels of each valence level are compared in the following manner:

$\boldsymbol{IF}$ $negative > max(positive, neutral)$ $\boldsymbol{THEN}$ $valence = negative$

$\boldsymbol{ELSE\ IF}$ $positive > max(negative, neutral)$ $\boldsymbol{THEN}$ $valence = positive$

$\boldsymbol{ELSE}$ $valence = neutral$

This conditional chain of logic applies a form of thresholding that ensures that the dominant of the valences prevails overall. Valences received by Phase II of the framework are in logarithmic form and converted to a base ten float form in Phase III prior to evaluation by this conditional chain. Because we are only interested in negative valence, valences that evaluate to positive or neutral are discarded for the purpose of presenting stress markers. This is done by binarizing the data such that overall negative valences are assigned 1 and all else are assigned '0'.

4.4 Quantifying Stress via Sensor Fusion

Moving toward sensor fusion for the purpose of representing stress, any combination of sensor data can be used to represent stress. To aid this process, sensor data is provided in both float and binary. For data such as GSR, HR, and valence, parsed and slightly processed forms of the data are dumped to file during Phase III. Phase IV then provides further processing via binarization of GSR peaks, heart rate, and emotional valence. Bit streams of each data set are initialized during Phase III, then modified appropriately during Phase IV of the framework. The following figures are logic circuits that illustrate how bit values are set for GSR, valence, and heart rate, respectively.

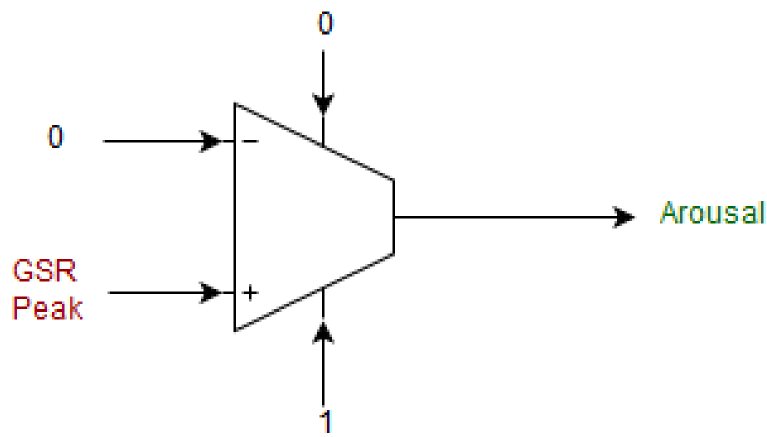

Figure 4.10: Logic circuit representation for binarizing arousal based on GSR peaks

Figure 4.10 illustrates arousal based on GSR peaks using a comparator that evaluates the presence of GSR peaks to produce an output that signifies arousal. If a GSR peak is present, the arousal output will be set to '1'; whereas an absence of a GSR peak would produce an output of '0'.

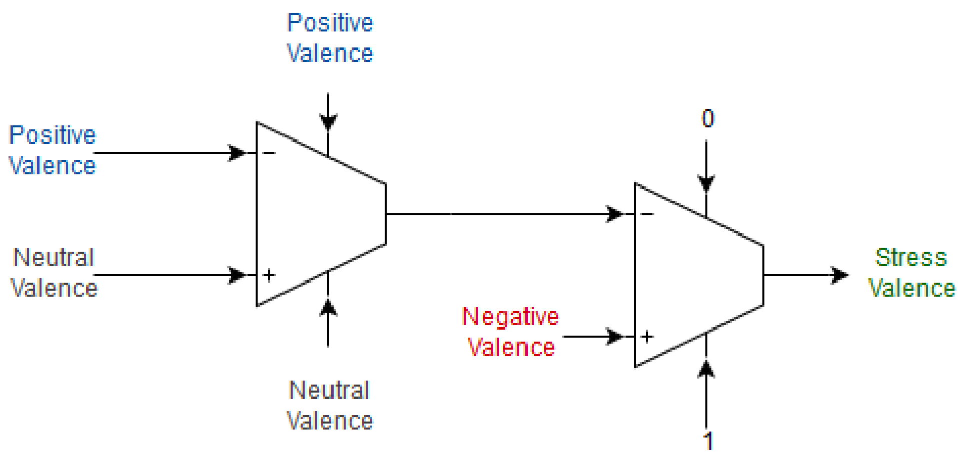

Figure 4.11: Logic circuit representation for binarizing stress based on emotional valence

Figure 4.11 illustrates stress valence based on emotional valence using comparators to evaluate the presence of negative valence. The first comparator outputs the maximum value between the detected positive and negative valences. If the negative valence is greater than the maximum value produced by the first comparator, the stress valence output will be set to '1'. However, if the detected positive or neutral valence is greater than the negative valence, the stress valence output will be set to '0'.

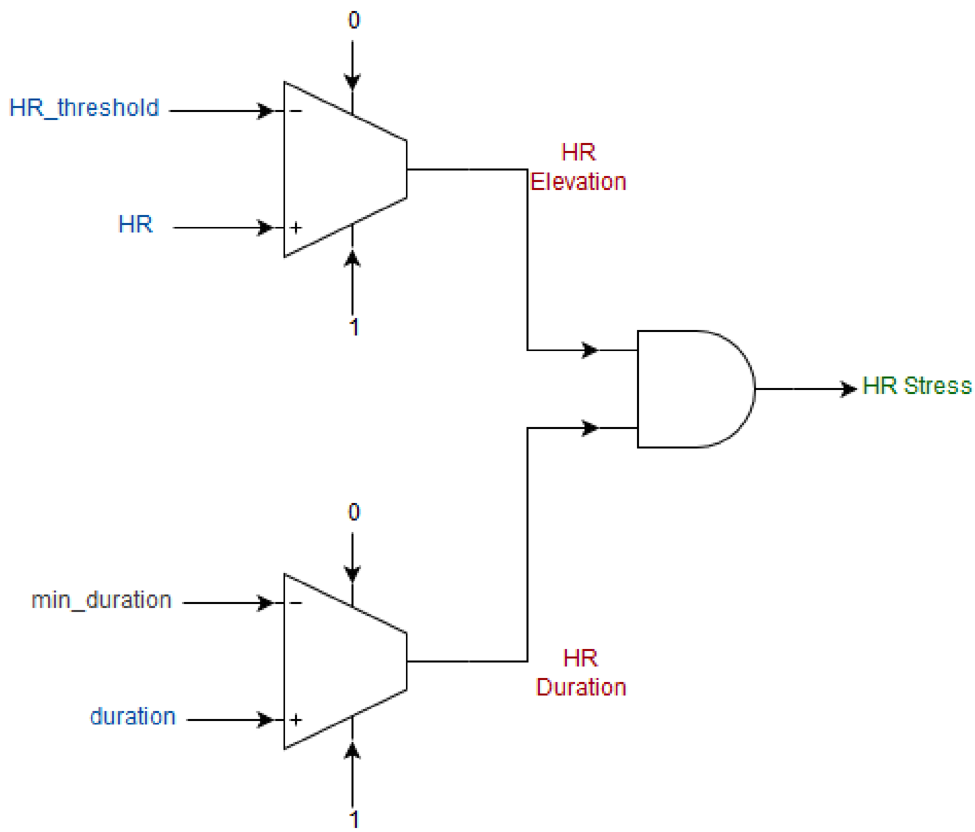

Figure 4.12: Logic circuit representation for binarizing stress based on heart activity (heart rate)

Figure 4.12 illustrates stress based on heart rate using a comparator that evaluates the presence of elevated heart activity. The stress logic takes in consideration two thresholds for heart activity: elevated heart rate and duration of elevated heart rate. These thresholds could be set for each respondent based on some training and knowledge of their normal resting heart activity. Using this logic, a stress output would only be set high ('1') if heart rate is elevated for a specified minimum period of time. All other cases would result in a low ('0') stress output.

Such logical circuit representation can be used as building blocks for forming larger logical circuits for representing stress. This application of what we are deeming "stress logic" can prove very useful in fusing sensor sources that have already been pre-processed. New stress logic circuits can be produced to represent different combinations of the sensor data collected and processed by the framework. Some examples are illustrated here.

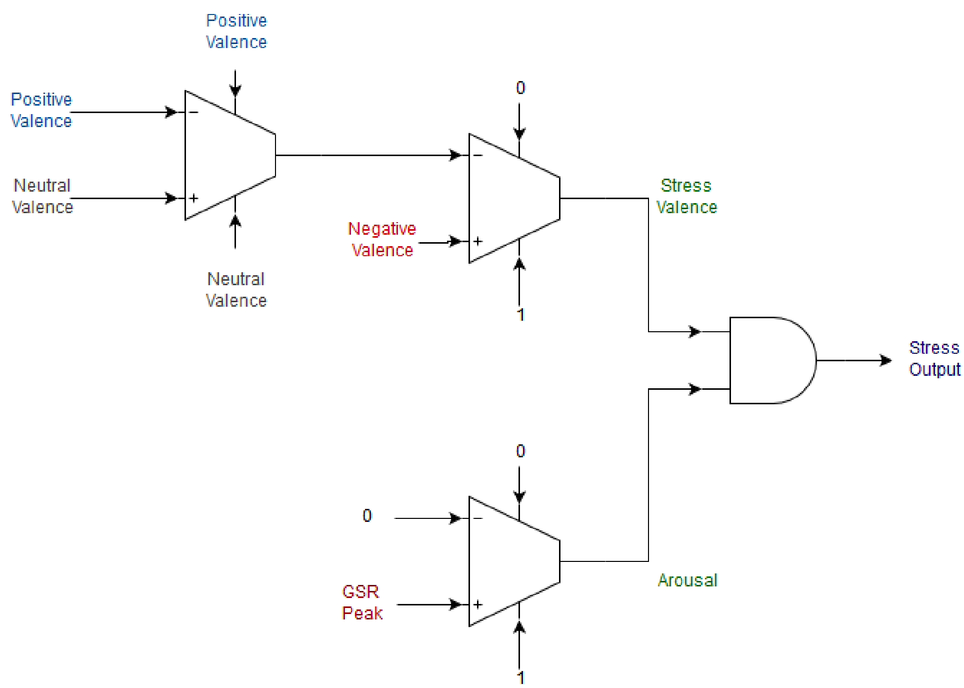

Figure 4.13: Illustration of stress logic combining emotional valence and GSR peaks

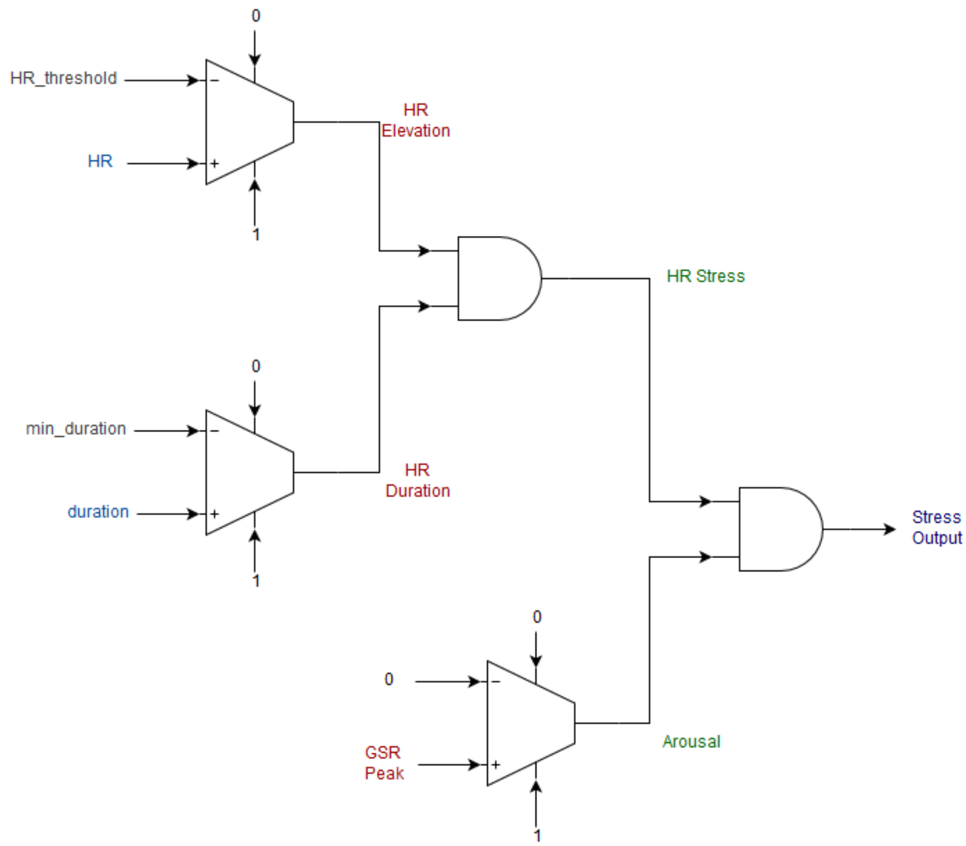

Figure 4.14: Illustration of stress logic combining heart rate and GSR peaks

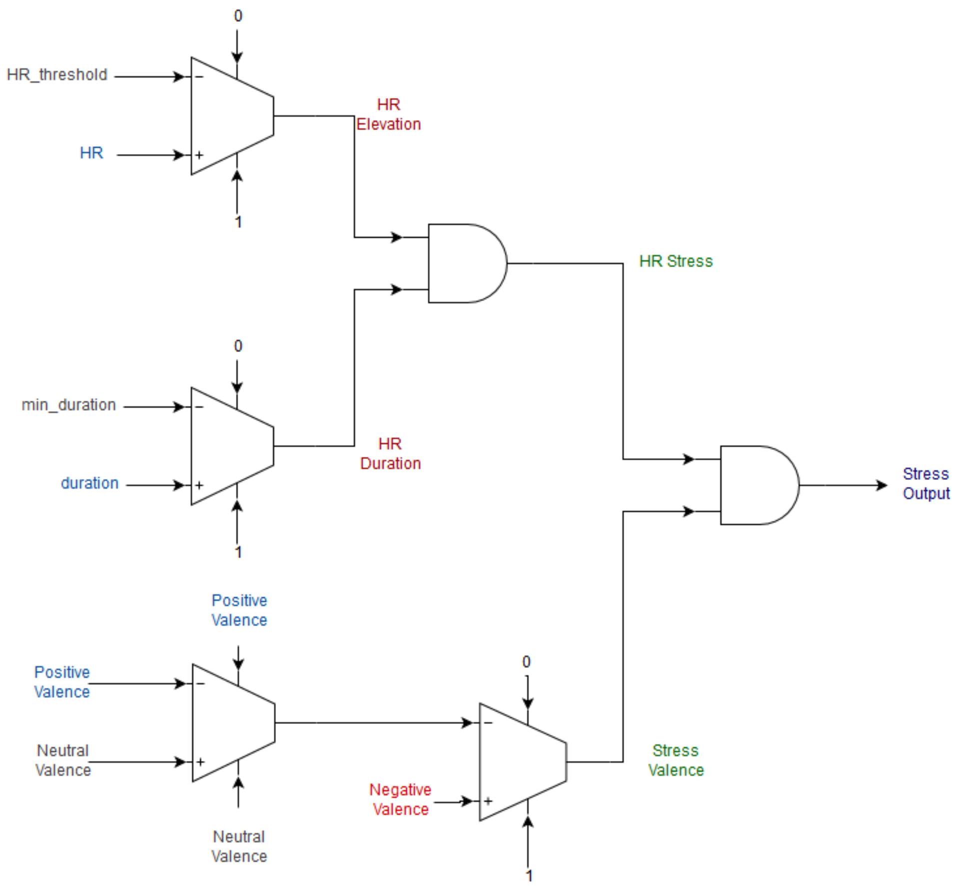

Figure 4.15: Illustration of stress logic combining heart rate and emotional valence

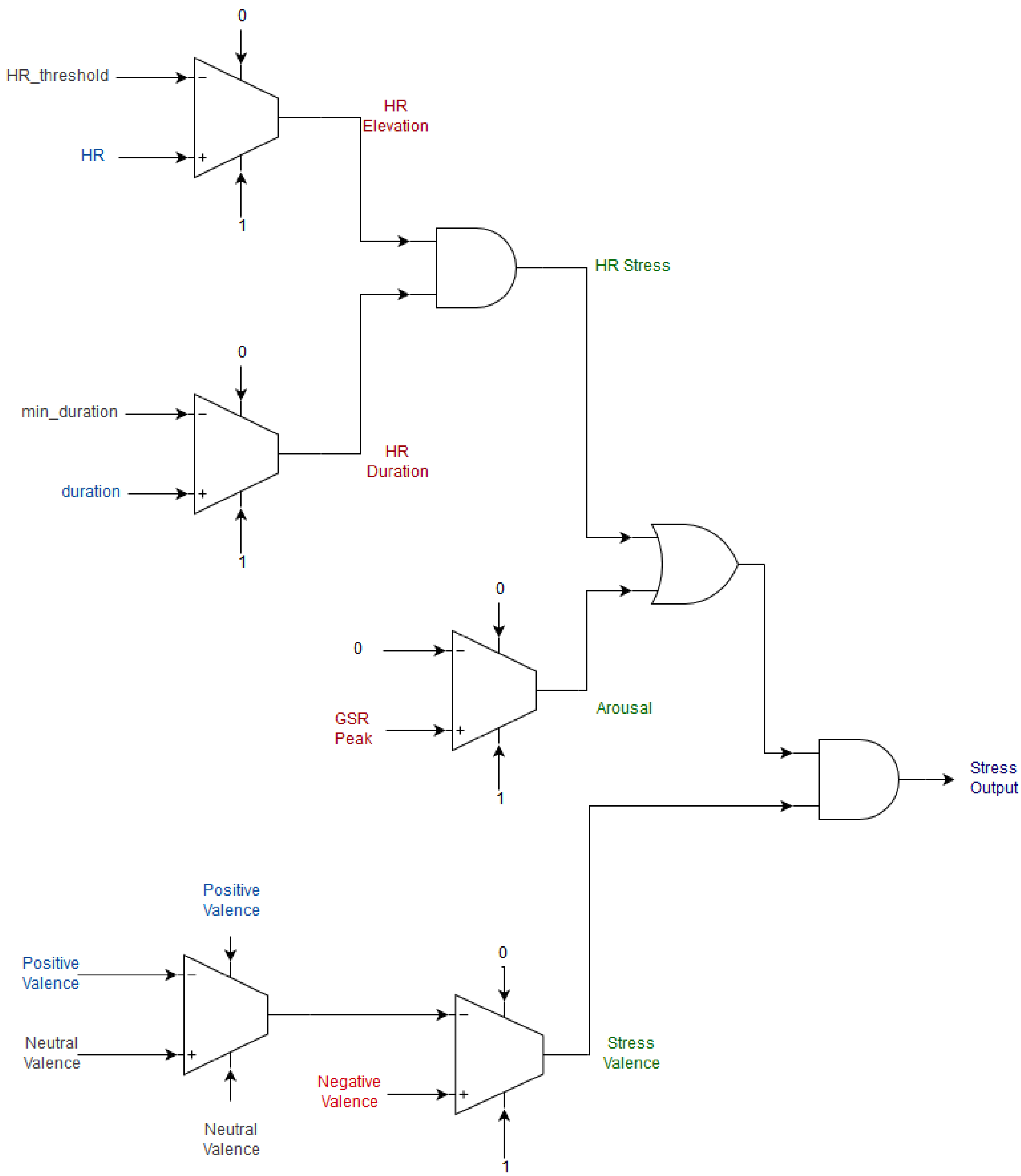

Figure 4.16: Illustration of stress logic combining heart rate, emotional valence and GSR peaks

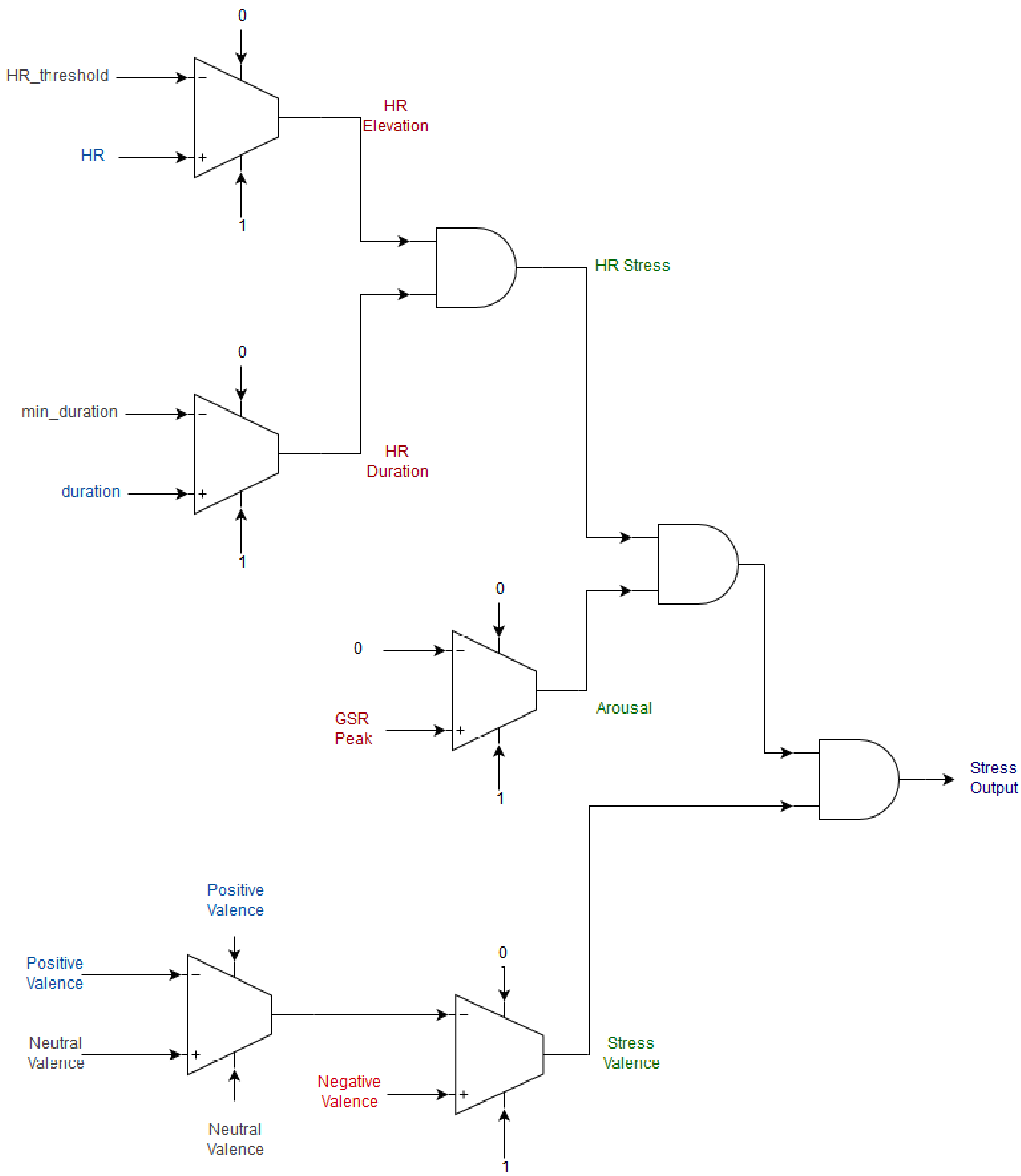

Figure 4.17: Illustration of stress logic combining heart rate, emotional valence and GSR peaks strictly using logical ANDs. This is a scenario when all sensor sources must produce positive outputs in order to generate a high ('1') stress output.

Based on these stress logic circuits, or some other means of data interpretation, stress scoring can then be developed. The following figure illustrates a stress score computed by the stress framework. It scores stress based on the percentage of bits designated high for presence of stress using the stress logic presented in *Figure 4.13* to interpret stress.

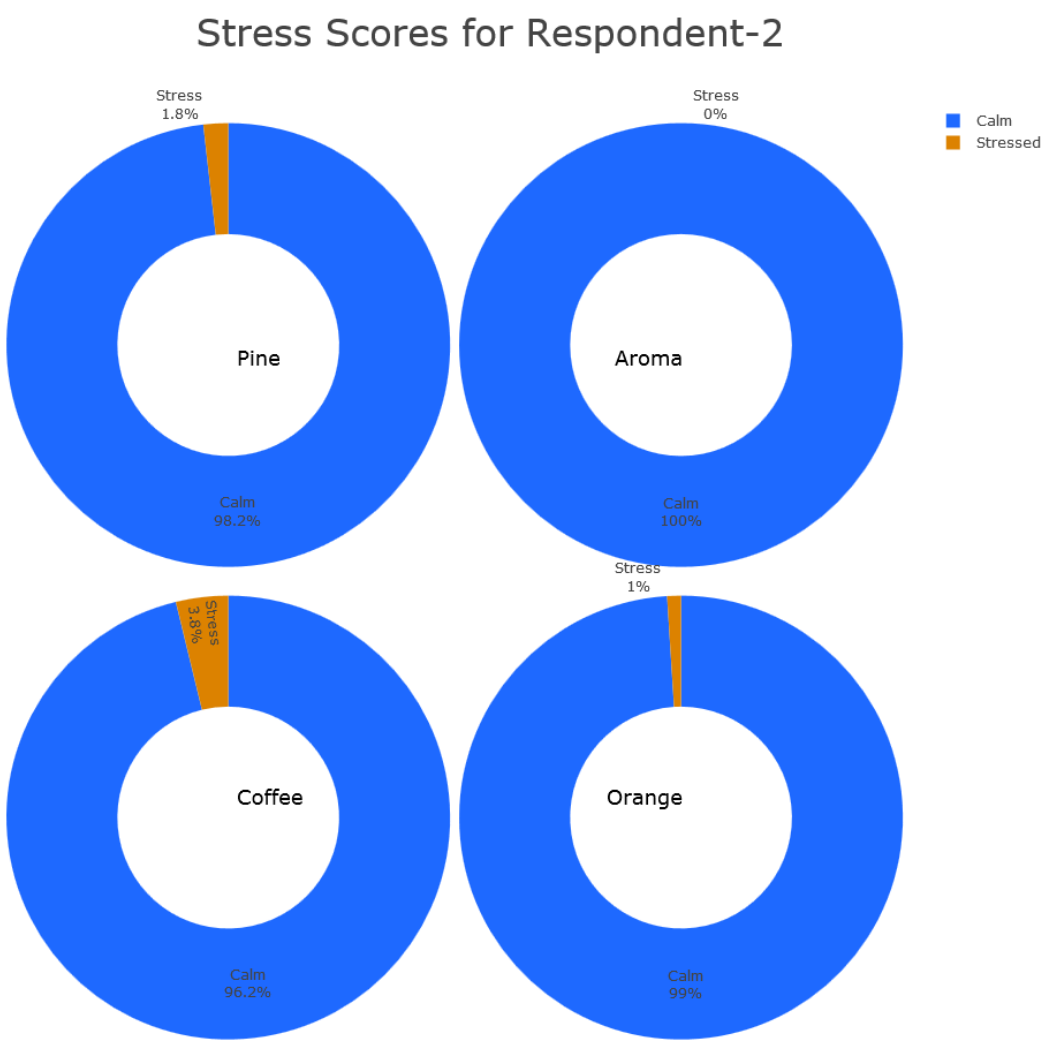

Figure 4.18: Illustration of quantified stress using binarized stress values. Sample data used was originally provided by iMotions (2016) [80], then plotted using custom software designed for this framework.

Alternatively, one could rate stress on a scale of 0 to 5, zero being no presence of stress (10 percent or less) and five being a very high level of stress (50 percent or higher).

The following logic could possibly be used for computing stress according to this scale based on the percentage of bits found high for stress:

$$\textbf{\textit{IF}}\ \%BITS_{HIGH} > 60\ \textbf{\textit{THEN}}\ stressscore = 5$$

$$\textbf{\textit{ELSE}}\ stressscore = floor(\%BITS_{HIGH}/10)$$

4.5 Paving Way toward an Automated TSST Protocol

Pulling this stress framework together with the aforementioned infrastructure for IoT-based fall detection is the connectedness of an HTTP network and voice automation provided by Amazon Alexa [84]. Though the core of the presented stress framework does not inherently require these two features, they allow for further automation of the framework and connectedness within a larger system geared toward health. Work toward such automation and connectedness has begun with integration of Amazon Alexa into the framework via a skill that automates the start of data collection within iMotions [80]. This Alexa skill was developed to utilize the external command protocol provided by the iMotions platform which allows for automation of certain actions such as starting data collection, advancing through stimuli presented to a respondent, and termination of data collection. At the time of this thesis only the initiation of data collection has been automated via Amazon Alexa and the HTTP server designed for the IoT-based infrastructure. As voice is commanded and interpreted through Alexa, HTTP requests are propagated from the Alexa skill to the HTTP server, then to iMotions to initiate sensor data collection and activation of the stress framework presented here. This is the start to development of a complete automation of the TSST protocol.

The TSST protocol is regarded as one of the most useful and appropriate standardized protocol for studies of stress hormone reactivity [4]. It employs several methods of measurements including heart rate, salivary cortisol, and self-reporting to assess stress. However, it is not limited to these three means of measurement. Other physiological and physical means of measurement such as ECG, EEG, EMG, GSR, AFEA, eye tracking and pupil dilation can be employed as well. The defining features of the TSST protocol, aside from physiological and physical measurements, is the timing and sequence of events for conducting a stress test. The protocol consists of four main portions: initial waiting period, pre-stress period, TSST core, and recovery. Stress measurements are taken at the beginning and end of the initial waiting period which form a baseline prior to any presentation of stimuli. Then a short pre-stress period is given as a buffer between the waiting period and TSST core. The TSST core consists of an anticipatory period immediately followed by speech and math tasks. The anticipatory period is meant to build up anxiety prior to performing psychologically stressful tasks such as presenting a speech and performing a series of difficult math problems. Stress measurements are taken during this time and specifically marked at the end of the TSST core as a reference point to compare against significant points of interest. The TSST core is then followed by two recovery periods in which no stimuli is presented and the respondent is allowed to relax. Stress measurements are taken at the end of each recovery period. An illustration of this protocol can be viewed in *Figure 4.19* below.

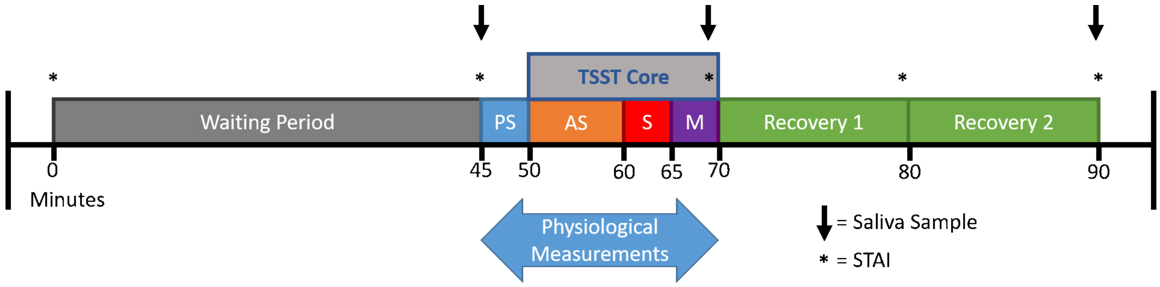

Figure 4.19: Illustration of the TSST Protocol. Trier Social Stress Test (TSST); State Trait Anxiety Inventory (STAI); 5-minute Pre-Stress period (PS); 10-minute Anticipatory Stress period (speech preparation) (AS); 5-minute Speech period (S); 5-minute Math period (M) [4]

With sufficient validation of sensor fusion against established benchmarks for determining stress, such as cortisol measurements and self-reporting, the combination of the iMotions platform with the IoT infrastructure and stress framework presented in this thesis can be used to form a new standard of assessing psychological stress in a non-invasive, automated manner.

Chapter 5

Conclusion and Future Work

Although recent advances in technology may seem to widen the gap between the young and the old, much of it can be used to benefit all ages. The internet of things has great potential to be of much more utility to older adults. With about 75% of older adults 45 and older wanting to stay at home as they age [85], the demand for home aid assistance is high. This is a perfect opportunity for smart home technology to fulfill some of the needs of this aging in place population.

As a smart fall detection system, the system described in this work has the potential to significantly improve the quality of life of millions of older adults who wish to live more independently within their own homes. The work presented in this paper provides a modular approach to fall detection that can be applied to a smart home environment. Hence, one of the extensions of the proposed work is to integrate this fall detection system into a smart home or facility. In addition to the modularity of the system, the incorporation of natural language adds a unique layer to fall detection. By allowing the user to communicate via voice to confirm falls and help direct a course of action, ease of use is allotted to the user. There is no need to press buttons or learn to use any associated software application. For this reason employing the use of natural language is ideal for older populations who may not be tech savvy.

The stress detection framework presented in this thesis can provide a non-invasive alternative to cortisol-based methods for stress detection using computing technologies such as GSR and facial expression analysis. The proposed work has the potential to automate stress protocols like the Trier Social Stress Test (TSST), as well as identify stress levels. With this in mind, the proposed framework can be used to run human trials to validate stress detection and management methodologies. At the composition of this thesis, an IRB (Institutional Review Board) is evaluating a proposal for human subject trials for this research, which will aim to accomplish such validation. Once these trials are conducted, the collected data could be analyzed and run through regressions to better understand correlation of quantified stress via the framework to that of golden standards (i.e. cortisol, STAI self-reporting). Once stress detection is established, the framework could aid in developing intervention components for stress management.

Moving toward further integration, these two developments can be modified to better complement one another. A possible scenario would be to use the stress detection framework as a predictor for falls, in which an older adult may exhibit signs of stress prior to a fall. This could potentially enhance the proposed fall detection infrastructure by adding a layer of prevention to the already established alert and monitoring system. Additionally, the stress detection framework could potentially be used for post assessment of falls via collection of physiological data. This may allow for a better understanding of post-fall behavior of the fallen respondent. Adding such provision for pre- and post-fall events could create a full solution system for fall prevention, monitoring, and post-assessment.

References

[1] Korhonen, N., Kannus, P., Niemi, S., Palvanen, M., & Parkkari, J. (2013). Fall-induced deaths among older adults: nationwide statistics in Finland between 1971 and 2009 and prediction for the future. *Injury*, 44(6), 867-871.

[2] CDC. (2016). *Important Facts about Falls.* http://www.cdc.gov/HomeandRecreationalSafety/Falls/adultfalls.html.

[3] Peavy, G. M., Jacobson, M. W., Salmon, D. P., Gamst, A. C., Patterson, T. L., Goldman, S., Galasko, D. (2012). The Influence of Chronic Stress on Dementia-Related Diagnostic Change in Older Adults. *Alzheimer Disease and Associated Disorders*, 26(3), 260266. http://doi.org/10.1097/WAD.0b013e3182389a9c

[4] Birkett, M. A. (2011). The Trier Social Stress Test Protocol for Inducing Psychological Stress. *Journal of Visualized Experiments?: JoVE*, (56), 3238. Advance online publication. http://doi.org/10.3791/3238

[5] Schlotz, W., Kumsta, R., Layes, I., Entringer, S., Jones, A., & Wst, S. (2008). Covariance between psychological and endocrine responses to pharmacological challenge and psychosocial stress: a question of timing. *Psychosomatic medicine*, 70(7), 787-796.

[6] MetLife. *Since You Care: Falls and Fall Prevention.* New York, NY: MetLife, 2007. Print.

[7] Maynard, S. R., Thapliyal, H., & Caban-Holt, A. (2015, December). Smart Home System for Patients with Mild Cognitive Impairment. In *Proceedings of the 2015 International Conference on Computational Science and Computational Intelligence (CSCI)* (pp. 738-742). IEEE.

[8] Mohanty, S. P., Choppali, U., & Kougianos, E. (2016). Everything you wanted to know about smart cities. *IEEE Consumer Electronics Magazine*, 5(3), 60-70.

[9] Chen, Leo. (2016). *State of the Medical Alert Industry.* http://www.consumersadvocate.org/medical-alerts/state-of-the-industry.

[10] Sixsmith, A., & Johnson, N. (2004). A smart sensor to detect the falls of the elderly. *IEEE Pervasive Computing*, 3(2), 42-47.

[11] Perolle, G., Fraisse, P., Mavros, M., & Etxeberria, I. (2006). Automatic fall detection and activity monitoring for elderly. *Proceedings of MEDETEL.*

[12] Lan, M., Nahapetian, A., Vahdatpour, A., Au, L., Kaiser, W., & Sarrafzadeh, M. (2009, April). SmartFall: An automatic fall detection system based on subsequence matching for the SmartCane. In *Proceedings of the Fourth International Conference on Body Area Networks* (p. 8). ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering).

[13] Huang, C. N., & Chan, C. T. (2014). A zigbee-based location-aware fall detection system for improving elderly telecare. *International journal of environmental research and public health*, 11(4), 4233-4248.

[14] Wang, J., Zhang, Z., Li, B., Lee, S., & Sherratt, R. S. (2014). An enhanced fall detection system for elderly person monitoring using consumer home networks. *IEEE transactions on consumer electronics*, 60(1), 23-29.

[15] He, J., Hu, C., & Wang, X. (2016). A smart device enabled system for autonomous fall detection and alert. *International Journal of Distributed Sensor Networks*, 2016, 1.

[16] American Physiological Association. (2016). *Stress: The different kinds of stress.* http://www.apa.org/helpcenter/stress-kinds.aspx.

[17] American Physiological Association. (2016). *How stress affects your health.* http://www.apa.org/helpcenter/stress.aspx.

[18] Krantz D.S., Whittaker K.S., & Sheps D.S. (2011). "Psychosocial risk factors for coronary artery disease: Pathophysiologic mechanisms. Heart and mind: The practice of cardiac Psychology. Washington, DC: APA.

[19] Pickering, T. (June 2001). Mental stress as a causal factor in the development of hypertension and cardiovascular disease. *Current Hypertension Report*, 3(3), 249-254.

[20] Monnikes, H., Tebbe, J., Hildebrandt, M., et al. (2001). Role of stress in functional gastrointestinal disorders. *Digestive Diseases*, 19, 201-211.

[21] Herbert, J. (1997). Fortnightly review: Stress, the brain, and mental illness. *British Medical Journal*, 315, 530-535.

[22] Andreou, E., Alexopoulos, E.C., Lionis, C., et al. (2011). Perceived Stress Scale: Reliability and Validity Study in Greece. *Int. J. Environ. Res. Public Health*, 8, 3287-329.

[23] Russell, E., Koren, G., Rieder, M., & Van Uum, S. (2012). Hair cortisol as a biological

marker of chronic stress: Current status, future directions and unanswered questions. *Psychoneuroendocrinology*, 37, 589-601.

[24] Hellhammer, D.H., Wst, S., & Kudielka, B.M. (2009). Salivary cortisol as a biomarker in stress research. *Psychoneuroendocrinology*, 34, 163-171.

[25] Picard, R.W. (1995). Affective computing. *M.I.T Media Laboratory Perceptual Computing Section Technical Report*, 321, 1-16.

[26] Picard, R. W. (1999, August). Affective Computing for HCI. *Proceedings of HCI* (1), 829-833.

[27] Picard, R. W. (2003). Affective computing: challenges. *International Journal of Human-Computer Studies*, 59(1), 55-64.

[28] Harmon-Jones, E., Price, T.F., & Gable, P.A. (2012). The influence of affective states on cognitive broadening/narrowing: Considering the importance of motivational intensity. *Social and Personality Psychology Compass*, 6(4), 314-327.

[29] Dishman, R.K., Nakamura, Y., Garcia, M.E., et al. (2000). Heart rate variability, trait anxiety, and perceived stress among physically fit men and women. *International Journal of Psychophysiology*, 37, 121133.

[30] Karim, N., Hasan, J.A., & Ali, S.S. (2011). Heart Rate Variability A Review. *Journal of Basic and Applied Sciences*, 7(1), 7177.

[31] Robinson, B.F., Epstein, S.E., Beiser, G.D., & Braunwald, E. (1996). Control of heart rate by the autonomic nervous system: studies in man on the interrelation between baroreceptor mechanisms and exercise. *Circulation Research*, 19, 400411.

[32] Klabunde, R. E. (2016). Electrocardiogram Leads. http://www.cvphysiology.com/Arrhythmias/A013.htm.

[33] Acharya, U.R., Joseph, K.P., Kannathal, N., et al. (2006). Heart rate variability: a review. *Med Bio Eng Comput*, 44, 1031-1051.

[34] Healey, J.A., & Picard, R.W. (2005). Detecting Stress During Real-World Driving Tasks Using Physiological Sensors. *IEEE Transactions on Intelligent Transportation Systems*, 6(2), 156-166.

[35] Harvard Health Publications. (2016). *Understanding the stress response.* http://www.health.harvard.edu/staying-healthy/understanding-the-stress-response.

[36] Lincoln, D.W. (1969). Correlation of unit activity in the hypothalamus with EEG patterns associated with the sleep cycle. *Experimental Neurology*, 24(1), 1-18.

[37] Horlings, R., Datcu, D., & Rothkrantz, L.J. (2008, June). Emotion recognition using brain activity. In Computer systems and technologies and workshop for PhD students in computing, *Proceedings of the 9th international conference on* (p. 6). ACM.

[38] Trans Cranial Technologies Ltd. (2012). 10/20 System Positioning Manual. Wanchai, Hong Kong: Trans Cranial Technologies Ltd.

[39] Sulaiman, N., Taib, M.N., Lias, S., et al. (2011, March). EEG-based stress features using spectral centroids technique and k-nearest neighbor classifier. In *Computer Modelling and Simulation (UKSim),2011 UkSim 13th International Conference on*, (pp 69-74). IEEE.

[40] Psychlab. (2016). *Skin Conductance Explained.* http://www.psychlab.com/SC_explained.html.

[41] iMotions. (2015). *What is GSR (galvanic skin response) and how does it work?* https://imotions.com/blog/gsr/.

[42] Empatica, Inc. (2016). *What should I know to use EDA data in my experiment?* https://support.empatica.com/hc/en-us/articles/203621955-What-should-I-know-to-use-EDA-data-in-my-experiment-.

[43] Picard, R.W., Fedor, S., & Ayzenberg, Y. (2016). Multiple arousal theory and daily-life electrodermal activity asymmetry. *Emotion Review*, 8(1), 62-75.

[44] Poh, M.Z., Swenson, N.C., & Picard, R.W. (2010). A wearable sensor for unobtrusive, long-term assessment of electrodermal activity. *Biomedical Engineering, IEEE Transactions on*, 57(5), 1243-1252.

[45] Peper E, Harvey R, Lin I, et al. (2007). Is there more to blood volume pulse than heart rate variability, respiratory sinus arrhythmia, and cardio-respiratory synchrony? *Biofeedback*, 35(2), 5461.

[46] Allen, J. (2007). Photoplethysmography and its application in clinical physiological measurement. *Physiological measurement*, 28(3), R1.

[47] Zhai, J., & Barreto, A. (2006, May). Stress Recognition Using Non-invasive Technology. In *FLAIRS Conference* (pp. 395-401).

[48] Empatica, Inc. (2015). *Have you done comparative studies or validation of the heart rate obtained from the E3?* https://support.empatica.com/hc/en-us/articles/200293658.

[49] Giardino, N.D., Lehrer, P.M., & Edelberg, R. (2002). Comparison of finger plethysmograph to ECG in the measurement of heart rate variability. *Psychophysiology*, 39(2), 246-253.

[50] Selvaraj, N., Jaryal, A., Santhosh, J., et al. (2008). Assessment of heart rate variability derived from finger-tip photoplethysmography as compared to electrocardiography. *Journal of medical engineering & technology*, 32(6), 479-484.

[51] Bolanos, M., Nazeran, H., & Haltiwanger, E. (2006, August). Comparison of heart rate variability signal features derived from electrocardiography and photoplethysmography in healthy individuals. In *Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE* (pp. 4289-4294). IEEE.

[52] Lundberg U., Kadefors R., Melin B., et al. (1994). Psychophysiological Stress and EMG Activity of the Trapezius Muscle. *International Journal Of Behavioral Medicine*, 1(4):354-370.

[53] Popović, M. B. (2013). Sensing in Robotics and Biomechanics. In *Biomechanics and robotics* (pp. 93-95). Boca Raton,FL: CRC Press.

[54] Wientjes, C.J. (1992). Respiration in psychophysiology: methods and applications. *Biological psychology*, 34(2), 179-203.

[55] Grossman, P., Wientjes, C.J. (1989). Respiratory disorders: asthma and hyperventilation syndrome. G. Turpin (Ed.), *Handbook of clinical psychophysiology.* Wiley, Chichester.

[56] Padasdao, B., & Boric-Lubecke, O. (2011, August). Respiratory rate detection using a wearable electromagnetic generator. In *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE* (pp. 3217-3220). IEEE.

[57] Lerner, J.S., Dahl, R.E., Hariri, A.R., & Taylor, S.E. (2007). Facial expressions of

emotion reveal neuroendocrine and cardiovascular stress responses. *Biological psychiatry*, 61(2), 253-260.

[58] Ekman, P., O'Sullivan, M., Friesen, W.V., & Scherer, K.R. (1991). Invited article: Face, voice, and body in detecting deceit. *Journal of nonverbal behavior*, 15(2), 125-135.

[59] Cohn, J. F., Ambadar, Z., & Ekman, P. (2007). Observer-based measurement of facial expression with the Facial Action Coding System. *The handbook of emotion elicitation and assessment*, 203-221.

[60] Martin, K.B., Messinger, D.S., & Prince, E.B. (2015). Facial Action Coding System.

[61] Mitra, S., & Acharya, T. (2007). Gesture recognition: A survey. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 37(3), 311-324.

[62] Lien, J.J., Kanade, T., Cohn, J.F., & Li, C.C. (1998, April). Automated facial expression recognition based on FACS action units. In *Automatic Face and Gesture Recognition, 1998. Proceedings. Third IEEE International Conference on* (pp. 390-395). IEEE.

[63] Tian, Y.L., Kanade, T., & Cohn, J.F. (2005). Facial expression analysis. In *Handbook of face recognition* (pp. 247-275). Springer New York.

[64] MIT Media Lab. (2016) Professor Rosalind W. Picard, Sc.D. http://web.media.mit.edu/ picard/.

[65] Affectiva. (2014). Automated Facial Coding: Delivering Easy & Affordable Neuroscience Insights [White paper]. Retrieved May 25, 2016 from Affectiva: http://www.affectiva.com/wp-content/uploads/2014/09/White_Paper___Automated_Facial_Coding.pdf.

[66] McDuff, D., Kaliouby, R., Senechal, T., et al. (2013). Affectiva-MIT facial expression dataset (AM-FED): Naturalistic and spontaneous facial expressions collected. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops* (pp. 881-888).

[67] Chen, L., Yoon, S.Y., Leong, C.W., et al. (2014, November). An initial analysis of structured video interviews by using multimodal emotion detection. In *Proceedings of the 2014 workshop on Emotion Representation and Modelling in Human-Computer-Interaction-Systems* (pp. 1-6). ACM.

[68] Littlewort, G., Whitehill, J., Wu, T., et al. (2011, March). The computer expression recognition toolbox (CERT). In *Automatic Face & Gesture Recognition and Workshops (FG 2011), 2011 IEEE International Conference on* (pp. 298-305). IEEE.

[69] Barreto, A., Zhai, J., & Adjouadi, M. (2007). Non-intrusive physiological monitoring for automated stress detection in human-computer interaction. In *HumanComputer Interaction* (pp. 29-38). Springer Berlin Heidelberg.

[70] Haak, M., Bos, S., Panic, S., & Rothkrantz, L.J.M. (2009). Detecting stress using eye blinks and brain activity from EEG signals. *Proceeding of the 1st driver car interaction and interface (DCII 2008)*, 35-60.

[71] Partala, T., & Surakka, V. (2003). Pupil size variation as an indication of affective processing. *International journal of human-computer studies*, 59(1), 185-198.

[72] Alshehri, M., & Alghowinem, S. (2013, October). An exploratory study of detecting emotion states using eye-tracking technology. In *Science and Information Conference (SAI)*, 2013 (pp. 428-433). IEEE.

[73] Alghowinem, S., AlShehri, M., Goecke, R., & Wagner, M. (2014). Exploring eye activity as an indication of emotional states using an eye-tracking sensor. In *Intelligent systems for science and information* (pp. 261-276). Springer International Publishing.

[74] Bekele, E., Zheng, Z., Swanson, A., et al. (2013). Understanding how adolescents with autism respond to facial expressions in virtual reality environments. *Visualization and Computer Graphics, IEEE Transactions on*, 19(4), 711-720.

[75] Mountain State Centers for Independent Living. (2016). *Understanding and Dealing With Stress.* http://www.mtstcil.org/skills/stress-deal.html.

[76] The American Institute of Stress. (2016). *Stress Effects.* http://www.stress.org/stress-effects/.

[77] Piana, S., Mancini, M., Camurri, A., Varni, G., & Volpe, G. (2013). Automated analysis of non-verbal expressive gesture. In *Human Aspects in Ambient Intelligence* (pp. 41-54). Atlantis Press.

[78] Shimmer Sensing. (2016). Consensys GSR Development Kits. http://www.shimmersensing.com/shop/gsr-optical-pulse-development-kit.

[79] Jia, N. (2009). Detecting human falls with a 3-axis digital accelerometer. In Volume 43, Number 3, 2009 *A forum for the exchange of circuits, systems, and software for real-world signal processing* (p. 3).

[80] iMotions A/S (2016). GSR Pocket Guide. Retrieved from https://imotions.com/guides/ on 06/27/2016.

[81] Analog Devices (2009). The Five Motion Senses: Using MEMS Inertial Sensing to Transform Applications. analog.com.

[82] Lynch, J. P., Partridge, A., Law, K. H., Kenny, T. W., Kiremidjian, A. S., & Carryer, E. (2003). Design of piezoresistive MEMS-based accelerometer for integration with wireless sensing unit for structural monitoring. *Journal of Aerospace Engineering*, 16(3), 108-114.

[83] Amazon. (2017). Amazon Echo. https://www.amazon.com/dp/B00X4WHP5E/ref =ods_bn_cat_aucc_h3_echo

[84] Amazon Alexa. (2017). Alexa Voice Services. https://developer.amazon.com/alexa-voice-service

[85] Ramnarace, Cynthia. (2011). *Aging in Your Own Space.* AARP. http://www.aarp.org/home-garden/housing/info-01-2011/aging_in_your_own_space.html.

[86] 2016. IEEE. Reprinted, with permission, from Shalom Greene, IoT-Based Fall Detection for Smart Home Environments, *Nanoelectronic and Information Systems (iNIS), 2016 IEEE International Symposium on*, Dec. 2016

[87] 2016. IEEE. Reprinted, with permission, from Shalom Greene, A Survey of Affective Computing for Stress Detection: Evaluating technologies in stress detection for better health, *IEEE Consumer Electronics Magazine (M-CE)*, Oct. 2016

VITA

Education:

University of Kentucky

Dept. Electrical and Computer Engineering

MS Electrical Engineering 08/2014 – 05/2017

Rochester Institute of Technology

Dept. Electrical, Computer, & Telecommunication Engineering Technology (ECTET)

BS Computer Engineering Technology 09/2008 – 05/2013

Experience:

University of Kentucky

Department of Electrical and Computer Engineering

Teaching Assistant 08/2015 – 12/2016

Tempur-Sealy/Aerotek

EE Verification

System Integration Test Engineer (Contractor) 02/2014 – 08/2015

Lexmark International

Power Supplies and Sensors

Electrical/Hardware Engineering Intern 09/2013 - 01/2014

Firmware Development

Firmware Engineering Co-op 06/2013 – 08/2013

ASIC Development

Firmware Engineering Co-op 08/2012 – 11/2012

JADAK Technologies, LLC

Test Engineering

Test Engineering Co-op 12/2011 – 02/2012

Honors and Awards:

Lyman T. Johnson Diversity Award 09/2016 - 05/2017

Publications:

S. Greene, H. Thapliyal, and D. Carpenter, "IoT-Based Fall Detection for Smart Home Environments, IEEE International Symposium on Nanoelectronic and Information Systems, Gwalior, Dec 2016.

S. Greene, H. Thapliyal, and A. Caban-Holt, "A Survey of Affective Computing for Stress Detection", IEEE Consumer Electronics Magazine, Vol.5, No. 4, pp. 44-56, Oct 2016.