Biofeedback Tools for On-line Stress Detection and Reduction

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Abstract

This individual project aims to develop a real-time stress biofeedback tool using the physiological data collected by E4 wristband to detect individual’s stress level and help individual reduce stress through biofeedback method. The development of this tool is based on Xuanying Zhu’s real-time stress model and Nandita Sharma’s computational stress model developed in their thesis. Galvanic Skin Response and Blood Volume Pulse are selected as the input physiological data of this tool. E4 wristband is chosen as the physiological signals sensor to collect these two types of physiological data from user. After the data procession and calculation on the collected data over each second, a real-time stress curve which indicates user’s current stress level will be generated by the tool as a biofeedback to the user. This report firstly describes a literature survey which involves all the relevant studies conducted in this project to offer the necessary background knowledge and academic support. Then a detailed explanation on the real-time stress biofeedback tool is described, which includes the workflow, structure and construction of the tool. Upon the completion of the prototype of the tool, an evaluation on its performance is introduced as well. Lastly, due to the time limitation of this one semester individual project, the relevant future tasks to improve the performance of the developed tool prototype are concluded and explained in the future work chapter.
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1. Introduction

This chapter provides an introduction to the report. It presents the motivation, goals and tasks involved for the proposed development of a stress biofeedback tool based on the original real-time stress model constructed by Xuanying.

1.1 Motivation

Currently, many people face different kinds of stress on a daily basis. It can be described as the body’s psychological and physical reaction to the imbalance between the demands and resources available to a person [37]. Stress can be both positive and negative. Under some circumstances, stress can have a positive impact on an individual by causing mental and physical excitement, which can increase their focus and enhance their ability to study or work efficiently. Negative stress, however, can cause serious psychological and physiological problems, which may lead to physical and mental illness. For example, many students can feel particularly stressed when facing impending exams or assignment deadlines. If the stress endured by the student is excessive and prolonged, then he or she is more likely to develop anxiety that could negatively impact the performance of study. Therefore, there is currently a need for an effective method or tool that can be used to help people manage their stress.

Previously, Xuanying Zhu, a Master of Computing with Honours student mentored by Prof. Tom Gedeon at Australia National University (ANU), completed a thesis whose title is using physiological feedback to reduce observer stress. The first step in controlling and reducing stress involves the measurement of stress using mathematic values. Therefore, Xuanying developed a real-time stress model in her thesis that was used to calculate a stress degree value, which indicated a user’s stress level at the time of measurement. This was achieved by using certain types of physiological data collected from the sensors that were placed on the user. The findings from Xuanying’s project demonstrate that biofeedback is an appropriate method that can be used to help alleviate stress.

Previously, Xuanying used Neulog sensors to measure real-time stress, which are not portable and are overly sensitive to a user’s movement. However, the Research School of Computer Science at ANU now offers the Empatica E4 wristband, which is a new physiological sensor with advanced technology that can be worn on the user’s wrist like a watch. Therefore, it has the portability that the Neulog sensors did not have and is unaffected by user’s movement, allowing for the collection of real-time stress data at any time. This device has the potential to update Xuanying’s real-time stress model to
one that can serve as a real-time stress biofeedback tool, showing a user’s real time stress curve at any given place or time.

1.2 Main Tasks

The main goal of this individual project is to update Xuanying’s real-time stress model to a real-time stress biofeedback tool using the E4 wristband as new monitoring sensor. The detailed tasks to achieve this goal are described as follows:


b. Construct a software tool to collect physiological signals data from E4 wristband for real-time data streaming. Data includes Galvanic Skin Response and Blood Volume Pulse, as well as other accessible physiological signals data, such as Interbeat Interval and Skin Temperature.

c. Modify and update Xuanying’s original real-time stress model to work with the new data streaming interface developed in task (b), which is supposed to be the prototype of the real-time stress biofeedback tool.

d. Design software capable of collecting training data for the stress classifier re-training in the future.

e. Organize the ideas and make a plan to improve the prototype of the real-time stress biofeedback tool based on the experience in this project for future use.

f. Integrate all relevant code into the HCC workshop tool
2. Literature Survey

This chapter presents the background knowledge of this report and the previous work contributing to the development of this individual project.

2.1 Stress

The concept of “stress” was first scientifically introduced by Hans Selye in 1936, who defined it as “a complex reaction pattern that often has psychological, cognitive and behavioural components” [1]. The definition of stress can vary depending on the individual and the situation. Furthermore, how scholars define stress is also based predominantly on their field of study. This paper will focus on analysing the concept of stress in the medical and psychological fields, which define it as the human body’s psychological and physical reaction to the perceived imbalance between a circumstance’s demands and the resources available for coping with obstructions [2].

In 1974, Hans Selye divided stress into two categories, eustress and distress [3]. Eustress contributes to positive states, like hard-working and striving for goals, while distress causes negative states like anxiety, despair and even physical body damage [3]. Additionally, distress can be classified into further sub-categories based on the source and duration of the stress. One of the most common stress types is short-term or acute distress [4]. This kind of stress is usually caused by a sudden extreme fear, like witnessing a bad car accident or watching a horrible clip in a horror movie. In this situation, distress induces the body’s release of large amounts of adrenaline and cortisol for the emergency response. This enhances the individual’s strength, endurance and ability to react to imminent danger [4]. Typically, this short-term acute distress does not last long and the body will return to normal, assuming that the source of the stress has been removed. Given its short duration, acute distress generally does not cause physiological or psychological damage. However, it is possible for short-term acute distress to transform into long-term chronic distress if the individual is exposed to the stressor for a longer period or on a more frequent basis. Long-term chronic stress can cause considerable physical and mental damage to the human body. Sufferers of chronic stress may develop asthma, back pain, arrhythmias, fatigue, headaches, hypertension (HTN), irritable bowel syndrome, ulcers and a suppressed immune system [5].

When considering the effects caused by stress, it is apparent that a limited amount of stress can help encourage or motivate individuals to strive for goals. However, too much stress will significantly impact performance by decreasing concentration and attention levels, and weakening learning and decision making abilities [8]. Since short-term acute
distress is the most common and can develop into long-term chronic distress in some cases, this project aims to help people on detecting, measuring and controlling their short-term acute stress.

2.2 Stress Response

There are three main phases of the stress response, which are alarm reaction, resistance and exhaustion [6]. The first phase, alarm reaction, is initiated when the person recognises something as a threat. The autonomic arm of the peripheral nervous system will immediately give various orders to the human body by generating and signaling more hormones [7]. This communication system helps to prepare the human body so that it can react accordingly to incoming threats or dangers. The next phase, resistance, is caused by extended exposure to a stressor. Since an individual already recognises something as stressful, the level of physiological signaling is no longer as high as it was during the alarm reaction. The release of stress hormones is stabilised during this phase and the human body’s reaction capacity will decrease to a level slightly above baseline [7]. Prolonged exposure to stress, however, can lead to exhaustion because the body is in a constant, abnormal state of preparedness to deal with the perceived stressor. In this situation, the human body may become damaged and unable to resist the stress [6].

2.3 Relative Physiological Signals Measurement

The first step to help people manage their stress is to develop an accurate, reliable, real-time, and intuitionistic method to measure their stress level. The best way to measure this objectively is to monitor different physiological and physical changes in the human bodies that occur due to stress. Similar to XuanYing’s previous work, the focus of this project is to measure real-time stress by monitoring real-time changes in Electrodermal Activity (also called Galvanic skin response) and Heart Rate Variability.

2.3.1 Skin Conductivity

Skin conductivity, also known as electro-dermal response or psycho-galvanic reflex, represents the electrical conductance of an individual’s skin. This physiological signal changes according to the amount of sweat present on the skin. Typically, when a person experiences stress, he or she will perspire more, which increases the conductivity of the skin. Likewise, the skin conductivity will decrease when the person’s stress has been reduced [18].

The Galvanic skin response (GSR), which is determined by calculating the electrical potential between electrodes placed on the skin’s surface, is the most common and effective way to measure skin conductivity[19]. Similar to Xuanying, GSR data will be
used to construct the real-time stress biofeedback tool in this project [9]. Moreover, Xuanying already re-constructed Sharma’s stress degree classifier based the data pair of GSR and ECG data in Sharma’s training data set and this stress classifier is also supposed to be used in this project. Therefore, the GSR data has been chosen as one of the input data to be measured and processed in the real-time stress biofeedback tool.

2.3.2 Heart Rate Variability

Heart rate variability (HRV) is the physiological phenomenon involving a variation in the time interval between heartbeats. In her thesis, Xuanying selected this physiological signal as another stress indicator in her real-time stress model [9]. Furthermore, there are several studies published previously that used HRV as a primary measure for monitoring stress and assessing its effects on the human body [20-25]. Therefore, HRV has been chosen as another physiological signal to be applied to the real-time stress biofeedback tool. Figure 2.1 shows a strong relationship between HRV and stress level, which demonstrates that measuring HRV will serve as a good indicator of stress level.

![Heart Rate Variability](image)

**Figure 2.1 Relationship between HRV and stress level [36]**

HRV can be determined by recording Electrocardiogram (ECG), Blood Volume Pulse, ballistocardiograms,[26][27] and the pulse wave signal derived from a photoplethysmograph (PPG). In Xuanying’s project, ECG was chosen as the superior method to measure HRV because it excludes unnecessary heartbeats and displays a clear waveform [9]. Figure 2.2 shows an example of the ECG waveform recorded for one heartbeat, which has six labelled components (P, Q, R, S, T, and U). These waveform components indicate the electrical changes during one heartbeat. As seen in Figure 2.2, a single heartbeat starts with the contraction of the atria, which results in a change in electrical voltage as the P sub-wave shows. Following this, the “signal” passes through both the right and left atrium to the ventricles, where there is an elevated peak as QRS shows, caused by the depolarization of the ventricles. T and U represent the final parts of the heartbeat, which are irrelevant for heartbeat counting [28]. So each peak of QRS represents one heartbeat in an ECG curve.
However, the chosen E4 wristband sensor in this project does not have the ability to collect ECG data. It is only able to measure Blood Volume Pulse (BVP), which is the phasic change in blood volume with each heartbeat. When the heart pumps blood throughout the whole human body, the arteries of the wrist become more opaque, which allows less light to pass from the emitter on the E4 wristband through to the receiver. As shown in Figure 2.3, each heartbeat will be reflected by producing a peak on the BVP curve. Similar to ECG, BVP can be used to accurately measure heartbeat in real-time. Therefore, BVP has been chosen as the new physiological signal that will replace ECG as the input for the real-time stress biofeedback tool.

2.3.3 Physiological Sensor Update

As mentioned previously, Xuanying used Neulog GSR Logger Sensors in her project, whereas the newer E4 wristband from the Empatica Company will be used in this
project. The following table illustrates the main differences between these two sensors.

<table>
<thead>
<tr>
<th>Equipment</th>
<th>Streaming</th>
<th>Advantage</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Neulog</strong></td>
<td>USB wire connection</td>
<td>1. Allows real-time data streaming</td>
<td>1. Not portable/users can only sit with the equipment</td>
</tr>
<tr>
<td></td>
<td>Neulog software suite</td>
<td>2. High sampling rate on GSR data: 10Hz</td>
<td>2. Very sensitive to equipment movement</td>
</tr>
<tr>
<td>E4</td>
<td>Bluetooth wireless connection</td>
<td>1. Allows real-time data streaming</td>
<td>1. A low sampling rate on GSR data: 4Hz</td>
</tr>
<tr>
<td></td>
<td>Self-developed client with an official TCP server</td>
<td>2. Very portable</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. Not sensitive to equipment movement</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>4. High sampling rate on BVP data: 64Hz</td>
<td></td>
</tr>
</tbody>
</table>

**Table 2.1 Main differences between Neulog and E4**

In the future work section of her thesis, Xuanying proposed reducing the sensor’s sensitivity to user’s movement as a way to improve the accuracy of results [9].
Therefore, one goal of this project is to update the original real-time stress model by using a portable sensor that is not influenced by an individual’s movements. While the E4 wristband has a lower sampling rate on GSR data compared to the older Neulog sensor, it still has the capacity to collect both GSR and BVP data for the new real-time stress biofeedback tool with much less sensitivity to user’s movement.

2.4 Stress Management

At present, there is an increasing number of people reporting episodes of occasional stress. In addition, the proportion of people with major depressive disorder (MDD) or other mental diseases has risen significantly in recent years. In 2013, MDD affected approximately 253 million people worldwide, which accounts for 3.6% of the global population [10]. Therefore, the demand for appropriate stress management strategies is increasing rapidly. Current methods to control stress include progressive muscle relaxation [11], autogenic training [12], relaxation response [13], emotional freedom [14] and transcendental meditation [15]. This project will use the same biofeedback method as Xuanying’s previous work, which shows people their real-time stress level curve in order to help them control short-term acute stress.

Biofeedback is a method used to enable individuals to perceive bodily functions that are unconscious. By doing this, people gain the capacity to learn and modulate these activities in ways that may improve their overall health or their control ability on the mood [16]. During a biofeedback session, various physiological signals from an individual’s body will be monitored by sensors. Collected data will be processed, then direct and intuitional feedback will be given to the individual, which involves either a sound, a flash of light or an image representing the key features of the individual’s body. In this project, data points indicating the stress level over the past one second from real-time measurements will be used to create a stress curve. The participant will therefore be able to watch this real-time biofeedback stress curve and will attempt to control their stress on their own by using traditional relaxation methods, like deep breath, thinking about some happy things or other simple methods. Xuanying’s previous work demonstrated that these methods for stress management were both valid and efficient with biofeedback information’s help [9].

In order to help people control their stress efficiently and prevent the further negative influence of a short-term acute stress, the stress management work should be done during the second phase of human stress response, resistance, mentioned in Section 2.2. This requires a real-time biofeedback model to represent the stress level just with a little delay after individual firstly recognize the stress resource. To achieve the goals of this project, a real-time stress curve generator is required. In addition, participants must be taught how to use the biofeedback model prior to experiment initiation.
2.5 Bluetooth Wireless Connection

Bluetooth technology uses short-wavelength UHF radio waves in the ISM band from 2.4 to 2.485 GHz to achieve a short distance wireless data exchange [29]. At present, Bluetooth is managed by the Bluetooth Special Interest Group (SIG). There are currently more than 25,000 member companies in the areas of telecommunication, computing, networking, and consumer electronics of SIG [32]. SIG oversees specification development, manages the qualification program and protects the trademarks [33]. All manufacturers must meet Bluetooth SIG standards when marketing Bluetooth devices, which gives them all the capacity to connect with each other without any need for adjustment or modification. As shown in Figure 2.3, the E4 sensor used in this project has a built-in Bluetooth program, which allows the user to access real-time data directly in the EmpaticaRT app on his or her smartphone. At present, there is no official relevant software that is compatible with the E4 wristband for data streaming on Windows. The wristband’s Bluetooth module, however, still makes transferring data to a computer possible with a Bluetooth Dongle.

Given that its effective range is limited to 10 meters [31], all connected Bluetooth devices must remain in close proximity to one another. Generally, a master Bluetooth device can communicate simultaneously with a maximum of seven devices in a piconet, which is an ad-hoc computer network using Bluetooth connection. The devices can agree to switch roles in a Bluetooth connection. In the Bluetooth connection between a smartphone and E4 wristband, the E4 wristband works as the ‘master’, using its built-in function to send data to the smartphone under a specific mode (with blue light blinking on E4). The smartphone is the recipient of all physiological data and therefore serves as the ‘slave’ in this scenario. However, in this project, the computer carrying the real-time stress biofeedback tool is supposed to be the ‘master’ Bluetooth device, while the E4 wristband should work as ‘slave’ to get the command from user and give response. Given that the E4 wristband is not equipped with the necessary operating system to communicate with the computer directly, the sole way to stream data is to supply the instructions from the computer via an operable client.

2.6 Transmission Control Protocol

Transmission Control Protocol (TCP) is one of the primary procedures found on the Internet protocol suite. During the initial Internet implementation, TCP was developed to complement Internet Protocol (IP). In May 1974, researchers at the Institute of Electrical and Electronic Engineers (IEEE) introduced an internetworking protocol for sharing resources using packet-switching among the nodes, which is the prototype of the TCP used today [30]. TCP can deliver a stream of octets between applications running on hosts communicating within an IP network. It can achieve a reliable, ordered and error-checked message exchange between different Internet applications, including
the World Wide Web, email, remote administration and file transfer, which all rely on TCP.

TCP is a transport level protocol, while Bluetooth would be described as a lower level protocol. However, it is possible to use TCP in conjunction with Bluetooth to control a Bluetooth connected device. Although the Empatica Company does not offer a working software to stream real-time operations and data to Windows, it does offer a TCP server for users to achieve a protocol-based communication between the E4 wristband and Windows through a specifically designed BlueGiga BLED112 Bluetooth Smart Dongle (BLE Bluetooth dongle) [34]. Under the constraints of the TCP server, which is based on TCP socket connections, each TCP connection is permitted to link to only one Empatica Device at a time. The company recommends using the programming language, C#, for building the client on the Windows to work under TCP server. After a successful connection with a developed client, the server will wait for a formally formatted command message from this client. After receiving a valid command message, the server will provide relevant instructions to the E4 wristband and subsequently receive the response message to pass to the client. All of these message exchanges reply on the Bluetooth connection between the E4 wristband and BLE Bluetooth dongle. An relevant example of the type of transmitted response message is the real-time physiological signal data from the E4 wristband user. Therefore, the computer has the capacity to access the physiological signals and receive real-time data that is streaming from the E4 wristband.

2.7 Previous Work

This section contains a simple description and explanation on both Xuanying Zhu’s and Nandita Sharma’s thesis and models developed in their projects.

2.7.1 Sharma’s Stress Degree Classifier

During her PhD, Sharma developed the core stress degree classifier to make stress classification on a certain group of physiology signals [17]. For the initial part of her study, participants were asked to watch a series of either stressful or soothing, non-stressful film clips that each lasted approximately one minute. Various physiological signals were monitored during this period, including ECG, GSR, Blood Pressure (BP), eye gaze and pupil dilation. The stressful film clips featured scenes depicting distress, fear, and tension, while the non-stressful films included scenes of comfort, relaxation and meditation. Study participants were required to complete an evaluation form at the end of the experiment, detailing the stress levels experienced when watching each type of film.

Following statistical analysis, 215 statistic and measure values were derived and
normalised by individual to minimise the individual bias. Using these derived features as input, Sharma built several classification models, including Support Vector Machine (SVM) and Artificial Neural Network (ANN), for comparison and used a Genetic Algorithm to identify the best representative features among the 215 candidate features. Finally, the GA-ANN and GA-SVM models were proven to perform similarly in stress degree classification and GA also successfully selected a group of the best representative features according to the pre-set stopping criteria. Xuanying also selected Sharma’s GA-ANN model to construct and optimise the stress degree classifier used in her real-time stress model.

2.7.2 Xuanying’s Real-time Stress Model

Xuanying developed a real-time stress model using physiological feedback to reduce observer stress based on Sharma’s stress classifier [9]. Initially, the stress degree classifier used in Xuanying’s project was trained by only using GSR and ECG data. Because Xuanying want to accelerate the training phase of the classifier re-construction and reduce the time cost on each classification process to achieve real-time biofeedback, she only kept these two physiological signals as types of training data and real-time sampling data to generate stress curve. What’s more important, it is hard to find some real-time data streaming sensors on the other physiological signals such as eye gaze and pupil dilation. So Xuanying’s stress classifier can only “understand” the GSR and ECG data. Similar to Sharma’s strategy on constructing the original stress degree classifier, Xuanying firstly set the neuron network structure with only one hidden layer and selected Logistic function as the activation function. Meanwhile, a Genetic Algorithm was applied during the training phase to the feature selections among the 215 statistic and different values defined by Sharma previously, such as gradients, rate of change, mean, variance of GSR and ECG data, were measured. Finally 59 features from the 215 candidate features were been selected by GA as the best representative features to serve as the input data for the stress degree classifier. While the 59 input features were set, the relevant trained neuron network structure was also stored. By using 10-fold cross validation on Sharma’s training data set, the accuracy of this re-constructed stress classifier was tested as 81% which satisfied the requirements of the project [9]. Subsequently, the trained neuron network was later used as the stress degree classifier for Xuanying’s real-time stress mode. In addition, the selection results from the 215 candidate features were stored as a one-dimensional vector with 215 elements with values of either 0, which indicates that the corresponding feature is excluded and not going to be input to the neuron network, or 1, which signifies that the corresponding feature is one of the 59 filtered best representative features.

Xuanying created a stress curve generator once she had re-constructed Sharma’s stress degree classifier. Additionally, she used data spanning two seconds in order to ensure that the number of samples collected for feature derivation was appropriate for generating a precise stress index. Initially, Sharma’s code was used to derive 215
statistic and measure values defined by Sharma, and subsequently Xuanying used the stored vector which is the result of the GA on the features selection in classifier training phase to make the input vector for the trained stress classifier. Each of the filtered 59 feature values was set as an input for each of the 59 input neurons in the input layer of the neuron network. Finally, the trained neuron network generated a stress degree ranging from -3 and 3 by its calculation on the input data. By completing this process iteratively, a stress curve showing the stress degree of the user from the past two seconds was produced. In this project, the stress classifier constructed by Xuanying is directly used since there is no sufficient time to collect the new training data and then conduct a re-training on the current stress classifier. Even if enough training data has been collected which may also take over one month to design and conduct experiment, it will still cost over 3 month to apply the GA on feature selection to build a new stress classifier with the similar strategy used by both Xuanying and Sharma [9]. As this project is just a one semester individual project, the stress classifier replacement will not be considered.
3. Real-time Stress Biofeedback Tool

The real-time stress biofeedback tool developed in this project uses the E4 wristband to collect GSR and BVP data from the user. The data is then processed by using a trained stress classifier to calculate a stress index which is used to generate a real-time stress curve as biofeedback method. This will determine the user’s level of stress. In Xuanying’s previous study, she demonstrated that the degree of stress observed was reduced when the user was shown his or her stress curve in real-time [9]. Therefore, the primary function of this biofeedback method is to measure a user’s real-time degree of stress, while simultaneously helping them control the stress. The real-time stress biofeedback tool is composed of three parts, including a neuron network stress degree classifier, a stress curve generator and a real-time data streaming client originally developed in this project.

3.1 Real-time Data Streaming Client

Certain changes were made to the experimental procedure to improve upon Xuanying’s original real-time stress model. Firstly, a new sensor, the portable E4 wristband, was used to make monitoring physiological signals easier. Secondly, a client was created for the efficient and rapid streaming of real-time data. The TCP server, named as BLEServe, supplied by Empatica Company enables the transmission of signals straight from the E4 wristband to the Windows client exclusively via the Bluegiga BLED112 Bluetooth Smart Dongle. So the real-time data streaming client developed in this project is named as BLEClient. This facilitates the quick readout of physiological data in real-time as well as sending command message to E4 wristband.

![Figure 3.1 Bluegiga BLED112 Bluetooth Smart Dongle [34]](image)

All command script from the Windows client and response messages from the E4
wristband on the TCP server are limited to a canned format. Each relevant valid command will be explained in the BLEClient User Manual in the Appendix Chapter. The socket package in Virtual Studio 2015 is used to achieve a stable connection between the client and the TCP server. Furthermore, the introduction of a buffer facilitates the concurrent exchange of messages, while eliminating the chance of data loss. To transmit the signals from the sensor to the server, the E4 wristband is attached to the Bluetooth dongle by Bluetooth wireless connection. The client’s IP will be set to match the target IP in BLEServe. As shown in Figure 3.2, real-time data streaming is activated following connection by transmitting a specific command message through the client to the BLEServe then finally to the E4 wristband via Bluetooth connection between E4 wristband and dongle. As shown in Figure 3.3, the received response message will carry the real-time GSR and BVP data from the E4 wristband to the client, which will then be stored in a txt file.

![Diagram](image)

**Figure 3.2 How real-time data streaming client (BLEClient) works**

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**Figure 3.3 Sample of collected E4 wristband data format**

The rate of sampling from the E4 wristband for GSR and BVP data is 4Hz and 64Hz, respectively. The timestamp, in seconds, for the sample data is a measurement of the time interval from when the response message is received to the reference date, 1
January 1970, GMT. This is the raw data that will be pre-processed in the next phase.

### 3.2 Trained Stress Degree Classifier

Given that the sensor in this project has been updated, the input data of the stress biofeedback tool has been changed to GSR and BVP, where BVP is a new data type to be applied to the stress classifier. Furthermore, there is no BVP data in Sharma’s training data set. Therefore, it is anticipated that a re-training will be necessary on Xuanying’s stress degree classifier, which was trained by GSR and ECG data previously by Xuanying. However, given the time constraints of this one semester project, time is too limited to use the similar training strategy to Xuanying’s strategy using GA on features selection over 215 candidate features which is believed to take over 3 month. In addition, there is insufficient amount of training data on the new data pair, GSR and BVP, available to complete this re-training in a timely fashion. On the other hand, both the ECG data and BVP data are similar for representing the Heart Rate Variability (HRV) in the stress degree classification. Therefore, Xuanying’s original stress degree classifier will be used in this project as the core calculator of the real-time stress biofeedback tool. While the precision of the classification may be reduced by using BVP instead of ECG data as the input to the original stress degree classifier, it should not have a significant impact on its overall performance according to the previous description. However, a detailed re-training plan will still be presented to demonstrate how a better classifier will be trained in the future. This proposed re-training plan is based on Xuanying’s reconstruction plan of Sharma’s original stress degree classifier which can also help understanding how the Xuanying’s stress classifier was built previously. As shown in Figure 3.4, there are five main steps involved in reconstructing the stress degree classifier in the re-training plan.

![Figure 3.4 The process of training a stress degree classifier](image)

Firstly, large GSR and BVP training data sets are required. Each group in the training data set must be labelled manually with a specifically allocated stress degree. Training data sets will be obtained using a similar data collection strategy as the one used by Sharma in her thesis [17]. Training data will be loaded and pre-processed to eliminate any noise and outliers that may exist among each physiological signal type. Following the normalization of the data, a certain number of features, derived from the physiological signals data, will be calculated first. Then these features will be the candidate features and later filtered by GA to capture the most relative and decisive
ones for stress degree classification. The neuron network will then be trained for many times by applying each different group of selected features as input to neuron network. A considerable number of iterations on filtering relative features and training neuron network will be conducted to choose a best-performance trained classifier as well as a group of best representative features. After a complete training phase with GA, a group of the best representative features will be chosen in conjunction with a corresponding trained neuron network, which will serve as the best classifier structure. The weights matrices of the neuron network as well as the best representative features group will both be stored. This stored classifier will be regarded as the optimal stress degree classifier and will be used to decide a stress degree based on the collected real-time physiological data in a stress curve generator.

Figure 3.5 shows the structure of the neuron network served as the stress classifier. There are 59 input neurons in the input layer. The input of this neuron network will be the best representative features vector calculated by the past one-second data. Each element of the vector will be applied in a specific order to one of the 59 input neurons. Subsequently, this value will be passed by each single input neuron to all hidden neurons in the hidden layer.

Figure 3.5 The structure of the trained stress degree classifier [9]
There are 400 hidden neurons in the hidden layer. The input value of each hidden neuron will be calculated using the equation below [9]

\[ x = \sum_{i=1}^{n} w_i p_i \]

Where
- \( x \) is the input value of a hidden neuron
- \( n \) is the number of input neurons connected to this hidden neuron
- \( i \) is the \( i^{th} \) input neuron connected to this hidden neuron
- \( w_i \) is the weight of the \( i^{th} \) input neuron in the first weight matrix between input layer and hidden layer
- \( p_i \) is the output value of the \( i^{th} \) input neuron

Each hidden neuron processes the input value to generate its output value via an activation function which is represented by the equation below [9]

\[ y = \frac{1}{1 + e^{-x}} \]

Where
- \( y \) is the output value of a hidden neuron
- \( x \) is the input value of a hidden neuron
- \( e \) is the Euler’s constant, which is the base of natural logarithms

Once the output of each hidden neurons is calculated, the final step will involve calculating the output value of the neuron network using the equation below [9]

\[ S = \sum_{i=1}^{m} w_i y_i \]

Where
- \( S \) is the output value of the neuron network, which is also the value of the stress degree and will be used as a stress index to generate stress curve
- \( m \) is the number of hidden neurons connected to the output neuron
- \( i \) is the \( i^{th} \) hidden neuron connected to the output neuron
- \( w_i \) is the weight of the \( i^{th} \) hidden neuron in the second weight matrix between hidden layer and output layer
- \( y_i \) is the output value of the \( i^{th} \) hidden neuron

Once the stress index is calculated and stored, it is displayed by stress curve generator.
3.3 Stress Curve Generator

A stress curve generator is used to display a stress index for the development of a stress curve. The physiological signal data, GSR and BVP, is acquired by the user’s E4 wristband and is transmitted by the real-time data streaming client to be loaded by the stress curve generator. After data pre-processing, this stress curve generator uses the processed data to display a stress index showing the current stress degree of the tool user. By repeatedly yielding single stress index, a stress degree curve will be generated. As shown in Figure 3.6, a real-time stress curve is produced through five cyclical steps.

![Figure 3.6 The process of generating a real-time stress degree curve](image)

The process is initiated when data is loaded. In Xuanying’s project, the data sampling rate for Neulog sensors was 10Hz for both GSR and ECG signals. The previous two seconds of data are loaded in order to strike a balance between obtaining an appropriate number of samples and reducing stress curve delay. To satisfy sample size requirements, twenty sample points will be loaded for each physiological signal. Based on Xuanying’s previous work, this is a sufficient number of sample points for generating an accurate stress index. As mentioned previously, the E4 wristband sampling rate for GSR and BVP is 4Hz and 64Hz, respectively, which means that for one second of time, 4 GSR data points and 64 BVP data points will be collected. Since these rates are inconsistent, 4 GSR data points will be duplicated to 64 GSR data points to make 64 ordered pairs with each BVP data point. Using this strategy, 64 pairs of GSR and BVP data points will be obtained during each one second interval, which will allow for the development of an accurate stress index.

The next stage involves converting the scale of the input data values to match the training data values. The GSR data falls within a range of 0 and 30 in Sharma’s original training data set, which is similar to the data set used by the current stress classifier in this project. The numerical scale for the GSR data collected from the E4 wristband, however, ranges from 0 to 10. The equation below will be used for GSR data conversion.

\[
d_{i,new} = \frac{d_i - E_{min}}{E_{max} - E_{min}} \times (S_{max} - S_{min})
\]
Where
\(d_{i,new}\) is the new data after conversion
\(d_i\) is the data before conversion
\(E_{min}\) is the minimum value captured by E4 wristband
\(E_{max}\) is the maximum value captured by E4 wristband
\(S_{min}\) is the minimum value captured by Sharma’s Biopac sensors in training data set
\(S_{max}\) is the maximum value captured by Sharma’s Biopac sensors in training data set

At present, no training data set exists for the BVP data. As mentioned previously, the E4 wristband will also be used to gather the BVP data. In that case, the training and the real-time collected data will be in the same scale so a conversion will not be necessary if a new stress classifier is trained on the new training data. For now, a simple conversion will be applied to the BVP data so that the Xuanying’s stress classifier is compatible with the new sensor. The BVP data collected by the E4 wristband lands within a range from -100 to 100. Given that the values of ECG data in Sharma’s training data set range from 0 to 1, the BVP data value will be converted using the same GSR conversion equation presented above into a corresponding ECG data value. Since the meaning of using ECG and BVP data are both counting the heartbeats and being derived to the features indicating HRV, so it is believed that the direct replacement from ECG data to GSR is not supposed to impact the performance of the stress classifier significantly.

After data pre-processing, 59 representative features are derived by calculating the statistical and measures values of the one-second data and using the features choosing vector stored in the classifier training phase. Summary statistical values include the mean, standard derivation, skewness, interquartile range, minimum and maximum. Measures values reflect the number of peaks for periodic signals. The 59 features are those that have been selected by GA in the stress classifier training phase. They will be made into an input vector that will be applied to the trained stress degree classifier. Through the classifier’s calculation described in section 3.2, a stress index will be produced, showing the level of stress ranging from -3 to 3. Finally, a stress curve will be displayed by repeating this process.
4. Evaluation

This chapter delivers a simple evaluation of the performance of the stress biofeedback tool prototype developed in this project. Given that the stress classifier developed by Xuanying is still used in this project, it is unlikely that further experimental evaluation will be considered until a new and improved stress classifier, trained with GSR and BVP data, is available. There was already a detailed experimental evaluation of the current stress classifier conducted by Xuanying in her thesis [9].

A simple test on the stress biofeedback tool prototype has been conducted to ensure that the new sensors and data streaming interface can work effectively with the original stress classifier. Three male students were enrolled as test participants, all aged around 22 years old with no reported mental illnesses. Whilst wearing the E4 wristband, each participant was asked to view a different YouTube video showing different contents for around 400 seconds to 450 seconds. Before initiating the experiment, the participants were instructed to try to control their levels of stress using the biofeedback information offered by the real-time stress biofeedback tool, which is the real-time stress curve. They were suggested to use the general relaxation techniques, like deep breathing, to manage their stress if they find that their stress curve goes too high. Figures 4.1, 4.2 and 4.3 illustrate the stress curves collected for each participant.

![Stress Curve of Participant 1](image)

Figures 4.1 Stress Curve of Participant 1

Participant 1 was asked to watch a clip from a zombie movie. Though this participant said he likes zombie movies, his stress level showed by tool is still above 0 at most time which indicates he was a little anxious and stressful during the whole process. Then at around 250 second, there was suddenly a zombie who jumped out in the movie which lead to a significant increasing of his stress level to around 2.6 at that time. Then by showing this curve to him, he started to control his stress immediately with a strong...
consciousness. So the stress level decreased into the average level for the rest of the time.

![Figure 4.2 Stress Curve of Participant 2](image)

Participant 2 was asked to watch a clip from a car racing movie. This kind of movie clip should make people excited which should lead to a high average stress level. But since there was not any very incitant scene during the entire clip, there was not a high peak in this participant’s stress curve. He kept watching the movie and the stress curve at the same time, so his stress was controlled well. There were several times when he looked at the stress curve and tried relax consciously his stress level decreased significantly.

![Figure 4.3 Stress Curve of Participant 3](image)

Participant 3 was asked to watch a clip from a time-lapse video on nature scenery. This kind of video is believed to give people a comfortable and relax feeling. Then the stress curve of the participant shows his stress level kept being low during the test, where his stress level is smaller than 0 at most time. Whilst watching at his stress curve at same time, sometimes the stress level even got further decreased due to a conscious stress control.

The results obtained demonstrated that the stress biofeedback tool prototype performed accordingly. Furthermore, they showed that the new sensors and data streaming
interface work well with the original real-time stress model, illustrating that the prototype of the stress biofeedback tool was a success. Unfortunately due to time constraints, further experimentation was not possible. The stress level measurement accuracy of the tool actually relates to the precision of the stress classifier on stress degree classification. A similar experimental evaluation on the current stress classifier has already been performed previously by Xuanying [9]. The results from this project agree with those from Xuanying’s work. Both demonstrated that the biofeedback tool is capable of detecting stress in participants when exposed to a virtual environment. In addition, both studies illustrated that this tool can be used to help alleviate a user’s stress levels by offering them biofeedback information, which in this case was the real-time stress degree curve. While these findings are promising, further modifications and improvements are necessary to achieve a completed version of the stress biofeedback tool. As mentioned previously, this will require the future development of a new stress classifier trained by a new GSR and BVP training data set.
5. Future Work

Due to the time limitations of this one-semester project, there is still extensive work required to deliver a completed version of the stress biofeedback tool. This chapter will introduce some future directions.

5.1 New Training Data Collection

The current stress biofeedback tool uses a different type of input data compared to the previous real-time stress model developed by Xuanying. The present model utilises GSR and BVP data rather than the GSR and ECG data that was used previously. However, similar mathematical features of BVP to ECG data have been used in the new tool, which both indicate the features of HRV. Replacing ECG with BVP data as the source of input data is believed not to influence the stress classifier performance significantly. Therefore, an entirely new training data set of GSR and BVP data should be generated first to improve the current tool’s performance.

It is anticipated that an experiment, similar to one performed previously by Sharma, will be conducted in the future to collect labelled training data [17]. The intention is that all participants will be exposed to a variety of abstract virtual environments for the measurement of computational observer stress in Sharma’s standard at each specific virtual environment. Finally, a group of stress degree values within a range from -3 to 3 will be labelled with each participant’s GSR and BVP data set, which indicates a participant’s stress level during the entire experimental period. A large training set is required to appropriately train the neuron network. Based on the work previously conducted by Sharma and Xuanying, at least 30 participants should be enrolled in the project and sufficient time should be allocated to include diversiform virtual environments in each experiment.

To collect this training data set, the BLE client developed in this project has been updated to be able to conduct and evaluate such a data collection task. The usage of BLE client is detailed in BLE Client User Manual in the appendix chapter. In addition, while collecting GSR and BVP data, this client can be used to simultaneously measure other physiological signals as well, like skin temperature and Interbeat Interval. This data is also be possible to be used to assist the manual stress classification on the training data set.
5.2 Re-training Stress Classifier

Once an optimal amount of training data has been gathered, it will be used to re-train the stress classifier. The training strategy discussed in section 3.2 can be implemented again. Furthermore, Sharma and Xuanying only applied the Genetic Algorithm to the feature selection but not to the neuron network structure. If time permits, GA could be used initially for feature selection to derive the best representative features with only one hidden layer pattern net neuron network. Then, with the selected best representative features, the GA can also be used to select the best neuron network structure by finding the optimal number of the hidden layers and the number of hidden neurons in each hidden layer. While this process is expected to take a quite long period to complete, it should enhance the stress classifier’s overall function and performance significantly.

5.3 Experimental Evaluation

Following the completion of a new stress classifier based on GSR and BVP data, a group of experiment should be designed and conducted to evaluate the performance of the new stress classifier scientifically. Furthermore, it is anticipated that Xuanying’s stress classifier and the new stress classifier based on the GSR and BVP data will be compared on their performance. Following this, the completed version of real-time stress biofeedback tool with the new stress classifier should be tested in a real environment rather than an abstract virtual environment. The new portable E4 wristband sensor will enable test participants to move around rather than remain stationary throughout experimentation. This will allow the sensor to measure stress levels while participants perform real-life tasks, like taking exams or exercising at the gym. Therefore, the performance of the new stress biofeedback tool can be tested in real-life situations where users are exposed to a myriad of stressors. This will offer a comprehensive evaluation on the performance of the real-time stress biofeedback tool as well as the validity of Xuanying’s and Sharma’s thesis.
6. Conclusion

This chapter summarises the main outcomes of this project. The aim of this project was to develop a real-time stress biofeedback tool based on Xuanying’s real-time stress model. This section will also detail the progress that was made for each task initially set in Chapter 1.

This report presented a literature survey of topics that were relevant to this project, including stress identification, stress management, a description of physiological sensors and a summary of work conducted previously by Xuanying and Sharma. This research enhanced the author’s understanding of the subject. Furthermore, it provided an overview of the current real-time stress model and the basic thesis for biofeedback methods, as well as the relevant skills required for developing a new stress biofeedback tool.

A real-time data streaming client, BLEClient, has been developed to obtain the real-time streaming data from the E4 wristband. By working with a specific Bluetooth dongle and having the ability to communicate via protocol-based messages on BLEServe, all the physiological signals data relevant to the stress classification could be monitored in real-time and recorded on a Windows computer. This sensor has the capacity to measure four types of physiological signal, including Galvanic Skin Response, Blood Volume Pulse, Skin Temperature and Interbeat Interval.

A prototype of the real-time stress biofeedback tool was developed in this project. By making a new input data interface with the BLEClient, Xuanying’s original real-time stress model works perfectly with the new portable E4 wristband sensor. Several other modifications to Xuanying’s real-time stress model code were also made to ensure its functionality. The current tool’s newly developed BLEClient and input data interface has the capacity to efficiently pass the physiological signals data from the E4 wristband to the stress classifier on the computer. This data can then be rapidly processed into a stress curve to display the user’s real-time stress level. A simple test on this tool was also conducted in this project, which confirmed that the performance of this prototype tool was acceptable. Although it will be necessary to re-train the stress classifier on the new training data to develop a completed version of the real-time stress biofeedback tool.

The primary function of the BLEClient is to stream data for a trained stress classifier in order to generate a stress curve in real-time. In addition, it has the capacity to collect training data, which can subsequently be used to train a new stress classifier, based on GSR and BVP data. All of the relevant physiological signals data is simultaneously
transmitted by the client to the stress classifier as input and stored as a local txt file in a clear and formulated format. In the future, this client can be used in a training data collection task to gain a sufficient amount of sample labelled data for re-training.

Given the time constraints associated with a one-semester independent undergraduate project, training data on GSR and BVP could not be collected in a short time. Furthermore, the re-training task to construct a new stress classifier with the similar strategy to Xuanying and Sharma will still take over 3 months even if there is a sufficient training data set on GSR and BVP. However, these are the only tasks remaining to produce a complete and fully functional real-time stress biofeedback tool. The future plan for collecting the training data set and re-training the stress classifier is discussed in the future work chapter. This plan outlines the necessary steps required for the further improvement of this real-time stress biofeedback tool prototype. Last but not least, the developed code works from this project have also been integrated into the HCC workshop tool recorded as a prototype to be developed in the future.
7. Appendix

7.1 Independent Study Contract

INDEPENDENT STUDY CONTRACT

Note: Enrolment is subject to approval by the project co-ordinator

SECTION A (Students and Supervisors)

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<td>Qu</td>
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<tr>
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<td>Zheqi</td>
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<tr>
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<td>(may be co-mentor)</td>
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<tr>
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SEMESTER □ S2 YEAR: _2016_ □ S1 YEAR: _2017_
PROJECT TITLE: Biofeedback tools for on-line stress detection and reduction

LEARNING OBJECTIVES:
- Experience with construction of advanced experiment software interfaced to physiological devices
- Experience with design of user-centric computing experiment software design
- Experience with data analysis software

PROJECT DESCRIPTION:
- Literature survey
- Construct a software tool to collect and interpret physiological signals from users in real time
  - Design interface with
    - galvanic skin response (skin conductance), blood-volume pulse (heart rate),
    - electro-eyegromana and eye gaze devices (if time permits)
- Extend tool for bio-feedback control of stress to use each physiological sensor singly or together
- Design software to conduct and evaluate experiments to compare physiological sensors for the task
- Optional task: extend experiments to different feedback modes as well. (i.e. 3 modes x 3 sensors)
- Integrate all code into HCC Workshop tool
- Write report

Research School of Computer Science

Form updated Jun-12
ASSESSMENT (as per course’s project rules web page, with the differences noted below):

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MEETING DATES (IF KNOWN):
Weekly

STUDENT DECLARATION: I agree to fulfil the above defined contract:

.......................................................... .............................. 13 July 2016 ........................................
Signature                                           Date

SECTION B (Supervisor):
I am willing to supervise and support this project. I have checked the student’s academic record and believe this student can complete the project.

.......................................................... .............................. 13 July 2016 ........................................
Signature                                           Date

REQUIRED DEPARTMENT RESOURCES:

SECTION C (Course coordinator approval)

.......................................................... .............................. ..............................
Signature                                           Date

SECTION D (Projects coordinator approval)

.......................................................... .............................. ..............................
Signature                                           Date

Research School of Computer Science

Form updated Jun-12
7.2 BLEClient User Manual

**Introduction**

BLE client is a self-developed client for the Windows to link to the BLE TCP Server offered by Empatica Company. And BLE TCP server can achieve a protocol-based communication between E4 wristbands and Bluegiga BLED112 Bluetooth Smart Dongle which is the only permitted Bluetooth dongle for the BLE TCP server.

**Setup**

1. The BLED112 Bluetooth dongle should be firstly plugin on the computer, then user should download and install the newest version driver for the dongle.
2. User should download and install Empatica BLEServe software from Empatica Company official website. Besides, an API key is required to run this TCP Serve.
3. Use the purchase code of your E4 wristband to add it to the linked device list of your API
4. Run BLEServe and set serve port and serve address same as the pre-set address and port in the client.
5. If Bluetooth Dongle is working, then there be a message “Dongle connected” shown in BLEServe.
6. Turn on the E4 wristband and it will go in searching mode automatically (with a flashing blue light). Meanwhile click the start search button of the BLEServe.
7. If BLEServe successfully connects with the E4 wristband, your device’s ID will be shown on the device list.
8. Run the BLE Client and you can see the command window open.
9. Type in the command and press enter key to get the response.
10. To record all the response messages, you need to modify the text file path in AsynchronousClient.cs

**Commands and Response Messages Details**

All the following command messages are designed and formulated by Empatica Company. A message starts with R indicates it is a response message. And for C sharp, all the command is case-sensitive.
server_status
To check the current TCP server status.
Response Message:
R server_status OK
R server_status ERR <reason>

device_list
To check the list of current linked devices to the BLEServe by Bluetooth connection.
Response Message:
R device_list <NUMBER_OF_DEVICES> | <DEVICE_INFO_1> | <DEVICE_INFO_2>

device_connect <DEVICE_ID>
To let the client connect a specific device by DEVICE_ID, then be ready to receive, display and record the messages from this device.
Response Message:
R device_connect OK
R device_connect ERR <reason>

device_disconnect
To disconnect a specific device from the client by DEVICE_ID.
Response Message:
R device_disconnect OK
R device_disconnect ERR <reason>

device_subscribe <DATA_TYPE> ON
To start the data streaming of a specific data type
device_subscribe gsr ON
To start Galvanic Skin Response data real-time streaming
deviceSubscribe bvp ON
To start Blood Volume Pulse data real-time streaming
Response Message:
R device_subscribe <DATA_TYPE> OK
R device_subscribe <DATA_TYPE> ERR <REASON>

device_subscribe <DATA_TYPE> OFF
To shut down the current data streaming on a specific data type.
Response Message:
R device_subscribe <DATA_TYPE> OFF
R device_subscribe <DATA_TYPE> ERR <REASON>
pause ON
To suspend all the data streaming process.
Response Message:
R pause ON
R pause ERR <REASON>

pause OFF
To continue all the suspended data streaming process.
Response Message:
R pause OFF
R pause ERR <REASON>

**Data Streaming Message format**

E4_<DATA_TYPE> <TIMESTAMP> <DATA_VALUE>
Where <TIMESTAMP> is defined as time interval in seconds between the sample received and the reference date, 1 January 1970, GMT.

**Known Issues**

1. To make each experiment results distinguished, it is supposed to restart the client for each experiment and the txt file will also be overwritten if the previous txt file is created and existed.
2. The data streaming messages are also displayed in the command window to help user watch the streaming process directly. This will cause an inconvenience for typing in new command on the command Windows. Now this is still an initial version of the client. Such a problem can be solved by using the pause ON function to help user type in new command
Reference

National University, Canberra, 2013


[27] Brüser, Christoph; Winter, Stefan; Leonhardt, Steffen (2012). "Unsupervised Heart Rate Variability Estimation from Ballistocardiograms". 7th International Workshop on Biosignal Interpretation (BSI 2012), Como, Italy.


