DETERMINATION OF STRESS IN HUMANS USING DATA FUSION OF OFF-THE-SHELF WEARABLE SENSORS DATA FOR ELECTROCARDIOGRAM AND GALVANIC SKIN RESPONSE

by

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DEDICATION

I dedicate this work to my wife and child.
TABLE OF CONTENTS

LIST OF FIGURES.............................................................................................................................................6
LIST OF TABLES..................................................................................................................................................7
ABSTRACT..........................................................................................................................................................8
CHAPTER 1 PRELUDE.........................................................................................................................................9
  1.1 INTRODUCTION........................................................................................................................................9
  1.2 LITERATURE REVIEW.............................................................................................................................10
  1.3 SYNOPSIS.............................................................................................................................................13
CHAPTER 2 EXPERIMENT..................................................................................................................................14
  2.1 METHODS............................................................................................................................................14
  2.2 MEASUREMENTS...................................................................................................................................14
  2.3 VOLUNTEERS......................................................................................................................................17
  2.4 STRESS AROUSAL..................................................................................................................................18
  2.5 PROTOCOLS.......................................................................................................................................18
CHAPTER 3 TEMPLATE EXTRACTION...........................................................................................................21
  3.1 IDENTIFYING STRESS DURING THE EXPERIMENT........................................................................21
  3.2 TEMPLATE/TAGGING EXTRACTION.....................................................................................................21
CHAPTER 4 CLASSIFICATION TECHNIQUES.................................................................................................23
  4.1 STRESS DETECTION USING SCIENTIFIC APPROACH.....................................................................23
  4.2 LINEAR DISCRIMINANT ANALYSIS (LDA).........................................................................................23
  4.3 SUPPORT VECTOR MACHINE (SVM)....................................................................................................24
  4.4 MULTILAYER PERCEPTRON (MLP)......................................................................................................25
CHAPTER 5 RESULTS......................................................................................................................................26
  5.1 RESULTS..............................................................................................................................................26
CHAPTER 6 FUTURE WORK.............................................................................................................................28
  6.1 HOW TO IMPROVE THE SYSTEM.......................................................................................................28
  6.2 CONCLUSION......................................................................................................................................28
APPENDIX A.........................................................................................................................................................30
APPENDIX B........................................................................................................................................................35
APPENDIX C........................................................................................................................................................36
REFERENCE.....................................................................................................................................................73
LIST OF FIGURES

FIGURE 2.1 BMD101 ECG SENSOR ................................................................. 14
FIGURE 2.2 GSR v1.2 GSR SENSOR ............................................................. 14
FIGURE 2.3 BMD 101 USER INTERFACE ..................................................... 15
FIGURE 2.4 ECG WAVEFORMS ................................................................. 16
FIGURE 2.5 GSR WAVEFORM ................................................................. 17
FIGURE 2.6 A VOLUNTEER DURING THE EXPERIMENT ....................... 19
FIGURE 2.7 SAMPLE OF THE MONTREAL IMAGING STRESS TASK ........ 20
FIGURE 2.8 WONDERLIC TEST .............................................................. 20
FIGURE 3.1 TEMPLATE TAGGING ............................................................ 22
FIGURE 4.1 LINEAR DISCRIMINANT ANALYSIS ALGORITHM ................. 24
FIGURE 4.2 MULTILAYER PERCEPTRON SHOWING DIFFERENT LAYERS .... 25
LIST OF TABLES

TABLE 1.1 RESULTS OF ALL 25 VOLUNTEERS...........................................................................26
Abstract

Stress detection helps individuals understand their stress levels and advises them when to take a break from activities causing stress. Physical activities and environmental influences can affect a person’s stress levels. People with professions as first responders, pilots, and working parents with newborns are examples of people exposed to a large amount of stress. Acquisition and proper analysis of physiological data is helpful in managing stress. In this paper, the results from two sensors, electrocardiogram (ECG) and galvanic skin response (GSR) measurements, are fused to analyze stress in individuals; these sensors are noninvasive and wearable. Data from these sensors are collected simultaneously over a period of 25 minutes from 25 people which are undergoing a simulated stressor. Support Vector Machine (SVM) and Multilayer Perceptron (MLP) are used as the classifiers while Linear Discriminant Analysis (LDA) is used as the stress detection algorithm. The stress detection accuracy achieved varies with individuals and ranges from 87% to 95%. This approach of measuring stress is very suitable for real-time applications and can be used by practically anybody who wants to improve their performance.
CHAPTER 1 PRELUDE

1.1 Introduction

A century ago, the major threats to human existence were tuberculosis, flu, childbirth, and pneumonia [1]. The world we live in today is fast-paced and people seldom die from these diseases; instead, humans die of diseases that are relatively new, such as heart disease, diabetes, and cancer in addition to accidents and suicide. Most of these diseases are caused by stress or exacerbated by stress. Homeostasis is a state in which an organism or group is in balance [2]. When applied to humans, homeostasis means there is a level of glucose in the bloodstream that makes the body temperature balanced. With the advancement in technology which has led to the creation of smartphones, smart cars, TVs, and computers which help to reduce human effort, it is only logical to think that we live a stress-free life, but this is not the case. Stressors have increased and have caused low performance in the workforce, diseases, and harm to our wellbeing. A stressor is anything outside a human’s body that knocks an individual from its homeostatic balance [3].

Stress is the psychological perception of pressure and how the body responds to this pressure [5]. A stressful event can be caused by an internal or external phenomenon which leads to the release of adrenaline and cortisol. These hormones move through the body causing a change in heart rate, breathing, flow of blood and level of attention. The effect of stress leads to substandard work, poor health, depression and sometimes death. It is impossible to avoid stress, but excessive stress can be prevented by accurately measuring and developing a monitoring system to keep track and analyze the various stress hormones released by the body.

There are three categories of stress:

1) Acute stress: caused by a short-term factor.
2) Episodic acute stress: this is acute stress that occurs frequently.
3) Chronic stress: caused by a long-term factor.

Strenuous daily activities lead to acute stress which is not necessarily harmful but can reduce the performance of an individual in certain situations. Unchecked over a prolonged period, acute stress is harmful. The focus of this thesis is to identify acute stress in order to improve the productivity of individuals. The hormones released by the body during stress can be detected by various sensors such as Electroencephalography (EEG), Electrocardiogram (ECG), and Galvanic Skin Response (GSR). The focus is to use multiple sensors simultaneously to increase the accuracy of stress detection [e.g., ECG and GSR] and to provide feedback that helps an individual release the stress. An ECG sensor measures the heart rate (HR) in beats per minute (bpm) of an individual and the GSR sensor measures the electrical resistance of the skin caused by emotional stress in Siemens. A person undergoing stress undergoes an increase in breathing, heart rate, and palms become moist due to the increase in the sympathetic nervous system which causes an increased hydration in the sweat ducts [3].
Literature review

Chen et al. [15] used the hyperspectral imaging (HSI) technique to measure stress. This method is a non-contact method using human physiological response. HSI technique uses a camera to extract the tissue oxygen saturation (StO$_2$) value as a physiological feature for stress detection, which is done at a standoff distance from the subject. The HSI enables the imaging of a scene in hundreds of contiguous, narrow wavebands, with a bandwidth which is approximately 10nm, and in the visible and infrared regions of the electromagnetic spectrum to form image cubes with both spatial and spectral dimensions. The pixels within the image cube is split into three coordinates namely, two spatial coordinates ($x$, $y$), which are the location of pixels in 2D and a spectral coordinate ($\lambda$), which represents the wavelength. If the intensity of the reflected light is normalized to the incident light intensity for each image pixel, a characteristic reflectance spectrum of the object in the scene is obtained. HSI is different from photography in that photography uses three color channels (R, G, B) with wavebands on the order of 100nm, while HSI uses a narrow bandwidth for spectral sensing. The classification of objects in a scene is performed using textural features like shape, orientation, and intensity variation.

Adrenaline is secreted through the hypothalamic-pituitary-adrenal axis in response to a stressor, it binds to the adrenergic receptors of peripheral tissues, which prepare the body for the fight-or-flight response namely, acceleration of heart and lung actions, increase in blood pressure and stickiness, liberation of nutrients (glucose and oxygen) for muscular action and redirection of blood to provide fuel to the aroused brain, heart and muscles. These responses substantially increase the StO$_2$ and tissue oxygen content, although the increase can be transient or sustained. HSI can be used to sense StO$_2$ in vitro with the results represented in a spatial 2D StO$_2$ map. HSI StO$_2$ assessment is based on Beer-Lambert Law which relates absorption of light to the properties of the material through which the light is traveling.

The equipment used consisted of Headwall VNIR spectrograph combined with a PCO PixelFly camera and a home designed mirror scanning system. The spectrograph had a slit of 30µm which provided a maximum spectral resolution of approximately 5nm. The spectral sensitivity limit of the PCO camera ranged from 400 to 1000nm, with a maximum quantum efficiency yield of approximately 65 percent at 650nm, the opening angle of the PCO camera was 30 degrees. The dimensions of the entire HIS system was approximately 40 cm × 40 cm × 15 cm. The HSI system was placed 2 – 3 m away from the objects, a chest strap heart monitor (Garmin) was used to monitor the heart rate of each of subject during the experiment. It took 10 seconds (integration time 40ms, 250 scanning lines) to record one image cube, the StO$_2$ measurements come from the still images of the objects. This system does not operate in real-time.

Three psychological stressors were used for inducing stress, they are mental mathematics, public speaking, and recognition-memory task. One or all of these mental stimulations were applied to each participant until an increase in heart rate (continuous rise and at least a 6bpm increase compared with the initial heart rate) was observed. The stressors were sequential: mental arithmetic test, the memory test and then public speaking. They had twenty-one healthy subjects, with a mean age of 25 with nineteen of them been males and two females. The whole
experiment lasted for 25 minutes per subject, and halogen lamps were used as the sole illumination source during the experiment. HSI data was taken at specific times: at the beginning of the experiment, when the subject is relaxed (baseline) and when there was a constant increase in the subject’s heart rate (above 6bpm of the baseline). A cotton swab was chewed by all the participants at the baseline stage and also when the various stressors were applied. The subject was stressed for a total of 15 minutes during the 25 minutes period.

Analyzing the StO\textsubscript{2} results from all the subjects indicated that all 21 participants exhibited an increase in StO\textsubscript{2} level in the facial region, particularly in the forehead region when subjected to a psychological stressor. To investigate how StO\textsubscript{2} levels change due to the stressors, the average levels of 11 regions of interest ROI in the face was studied. The StO\textsubscript{2} levels for the forehead center region was calculated, each ROI contains pixels, with each pixel having an StO\textsubscript{2} value, therefore, producing an average StO\textsubscript{2} and a standard deviation value.

The HSI technique differs from my technique of measuring stress, their results are judged based on heart rate values which are relatively narrow (6 bpm). Although they use a cotton swab to measure cortisol, this result cannot be used simultaneously to corroborate the heart rate value. Also, perspiration and environment will affect any HSI equipment in that the oxygen in the blood or body changes with respect to environment, exercise and altitude. My approach uses a Galvanic Skin Conductance and Electrocardiogram thereby not basing my answer on one type of measurement.

Fernandes et al [13]. used blood pressure and galvanic skin response to detect stress, they based their measurement on the sympathetic nervous system which controls the conductance of the skin. Stress causes disruption of the autonomous nervous system which involves state of high sympathetic activation. An intense attention-grabbing and attention-demanding task will increase the galvanic skin response. The devices used are biofeedback GSR sensor, Remier M 2000 for blood pressure, ATMEGA 2560 microcontroller and an LCD screen.

A total of 25 subjects between the age of 18 – 24 years consisting of 17 males and 8 females were used for this experiment. The subjects were chosen with respect to their age because aging affects the blood pressure and heart rate. Each subject was first tested for their relaxed state (baseline), the GSR sensor only showed three levels: low 2 MΩ or higher, medium 1 MΩ and high 500 KΩ. These parameters determined if the subject was low stressed, medium stressed and high stressed, while the blood pressure baseline value for every subject was set at 135/85mmHg, anything higher was considered a stressed state. The subjects were stressed by making them run a flight of stairs, after the stressing session, the subjects were made to breathe slowly to get rid of panting or hyperventilation. Finally, the GSR and blood pressure of the subjects were recorded and compared with their baseline.

A before and after histogram was used to analyze the stress levels of all 25 subjects, the subjects were placed in three categories according to how they performed during the experiment: mentally stressed, physically stressed and normal. If the subject has a low blood pressure along with a low GSR value, it was concluded to be a normal condition, if the GSR level is high and the blood pressure is low, it was concluded to be a mental stress case and finally if the blood pressure is high and the GSR value is high, it is seen as a physical stress condition. 80 percent of the subjects
tested positive for physical stress with respect to both sensors while the rest tested positive for mental stress. They observed that doing exercise results in higher GSR level, it was not related to emotional or mental stress.

This approach of measuring stress is similar to mine in that they used a GSR sensor and a sensor which gives HR values. The major differences between my approach and this one is that they did not use any classifier, instead, they used histograms to analyze their data. They generalized (picked set values for blood pressure) when picking a baseline for their test subjects and finally, exercise does not affect psychological stress.

Bakker et al [9] used Galvanic Skin Response to measure stress, this method of measuring stress is a non-invasive method. This approach uses a sensor which is connected to your fingers or toes, from which data is collected. The main task was to determine whether the observed portion of the data collected contains a change that corresponds to an arousal. The purpose of arousal detection is twofold, the first is to obtain labels for the supervised learning process aimed at finding relationships between stress occurrences and external events of factors causing stress, the second purpose is to use an online detection mechanism in online or semi-online settings as an alarm for making the user aware of stress.

Two statistical methods are used in analyzing the GSR data, both approaches are aimed at finding significant changes in data. The first approach is called Fit which is based on monitoring the model error, and the second approach, ADWIN Adaptive Window, is based on monitoring the data itself. The Fit method uses a performance monitoring-based change detection with the non-parametric test. It was assumed that there is no global model that predicts the general GSR signal for a person, instead, they use a method that computes local models. They detected stress levels by monitoring the error of a locally fitted model, knowing the preprocessed data, their objective was to fit a simple regression model based on the observed Mean Squared Error for the incoming points. Using this method, they could determine a significant change in the prediction error. The ADWIN method works by checking if there are statistically significant differences between the means of each possible split of the sequence, if a difference is found, the oldest portion of the data backwards from the detected point is dropped and the splitting procedure is repeated until there are no significant differences in any possible split of the sequence.

GSR data was collected from 5 people over a course of 4 weeks, the device used was a watch-like device worn by the subjects during work hours (8 hours). The GSR used has a sampling rate of 4Hz resulting in a total of 72-time series of which 26 time series were excluded from the experiment due to the GSR level showed very low variation or the contact of the sensors was not sufficient to yield a usable signal. The remaining 56-time series were annotated for change points by visual inspection, they contained 368 change points with an average of 6.5 change points per time series.

The results showed that the Fit method detected more change points in the GSR data compared to the ADWIN method, but at a cost of false positives while the positioning of the change points is better handled by ADWIN. The ADWIN has a lower true positive rate because it does not detect small peaks and it does not detect the change in cases where the signal is slowly rising or falling.
This paper uses only one sensor to measure stress and the primary focus of the paper is to measure arousal in humans. In performing the experiment, the researchers did not use a detailed stressor in testing their subjects which led to inconsistencies in their results. Finally, the researchers concluded that the GSR sensor alone is not sufficient to measure stress in humans.

**Synopsis**

In the real world, there are a lot of sensors designed to measure these physiological signals. In other words, you can get a GSR and ECG sensor off the self. The problem with these sensors is that the Signal to Noise Ratio is not sufficient for an adequate measurement and getting a clear understanding of stress measurement using these sensors can be a challenge. This thesis addresses the collection of reliable data from the fusion of these off-the-shelve sensors and identifying any correlation when using these sensors to measure stress.
CHAPTER 2 EXPERIMENT

2.1 Methods
This section describes how the database was built, how the experiment was conducted, the criteria for picking a test subject, the type of psychological test used to stress the subject [1] and the manner in which an individual reacted to the stressor.

For this experiment, the researcher obtained an Institutional Review Board IRB certification and all the IRB requirements for the protection of human subjects were carefully followed. A copy of the consent form used for the IRB can be seen in the Appendix.

2.2 Measurements
The measurements were conducted at the Bioinstrumentation laboratory in the Department of Electrical and Computer Engineering at the University of Arizona. The workstation was grounded to prevent electrostatic discharge that may interfere with the data collection. The sensors used are BMD 101 module with a power source, Groove GSR sensor v1.2, and an Arduino UNO.

BMD 101 Module
- Frequency response: 0.5 – 100Hz
- Sampling rate: 512Hz
- Voltage: 3.7V
- Current: 20mA
- Communication mode: Bluetooth 2.1/serial port

Groove GSR v1.2
- Frequency response: 0.5 – 5Hz
- Sampling rate: 25Hz
- Voltage: 3.3 – 5V
- Current: 25mA
- Communication mode: USB serial port
The BMD 101 Module connects to a laptop via Bluetooth, when the 3 pins on the left (as seen on the BMD101 module image) are connected to a human via probes, the ECG PQRST waveform can be seen on a Graphic User Interface GUI created by SICHIRAY.

![ECG waveform](image)

*Figure 2.2 BMD 101 User Interface*

PQRST is the atrial and ventricular depolarization and repolarization of the heart [4]. The GUI also gives the real-time HRV, averaged HRV and a means to save the data. The HRV is calculated using R-R intervals [5].

The GSR sensor connects to a laptop via a USB port, and when connected to an individual’s finger outputs a single measure in real-time. Our skin gives away a lot of information on how we feel when we are exposed to emotionally loaded images, videos, events, or other kinds of stimuli [6].
No matter whether we are stressed, nervous, fearful, psyched up or surprised – whenever we are emotionally aroused, the electrical conductivity of our skin subtly changes [7]. One of the most sensitive measures for emotional arousal is GSR. GSR is measured in Siemens.
With the aid of ECG and GSR sensors in data collection, the Linear Discriminant Analysis (LDA) is used as a stress detection algorithm and the Support Vector Machine (SVM) is used as the classifier of the stressed and unstressed states, finally, the multilayer perceptron is used to verify the results obtained from SVM. In this thesis, the BMD 101 module was used for ECG data and the Groove GSR sensor v1.2 was used for GSR data, both sensors are off-the-shelf and were used to create the database. Knowing that humans react differently to the same event, this thesis models everyone separately thereby providing a scale to differentiate how an individual reacts to the stressor.

### 2.3 Volunteers

Volunteers were students at The University of Arizona as well as a professor, resulting in a total of 24 males and a female. The subjects age ranged from 21 to 70 years, with an average of 38 and a standard deviation of 3.15. All the subjects that participated in the experiment were
healthy, some of them are athletic. The reason for a few numbers of females is based on the fact that there are many more males in engineering and most females would not be comfortable having a man putting ECG probes on their chest.

2.4 Stress Arousal

Arousing stress in an individual necessitates a well-defined experiment in order to obtain an arousal to the specific stressor and for comparison to other individuals. This work induces stress by using a test anxiety strategy [9].

Test anxiety is a combination of physiological over-arousal, tension and somatic symptoms, along with worry, dread, fear of failure, and insufficient performance, that occur before or during test situations [12]. It is a physiological condition in which people experience extreme stress, anxiety, and discomfort during and before taking a test [10]. Test anxiety can also be labeled as anticipatory anxiety, situational anxiety or evaluation anxiety [10].

As a consequence, several physiological changes emerge: increased heart rate, stress hormone secretion, restlessness, and vigilance. In individuals, the degree to which an anxiety response is developed is based on the probability of bad things happening in the environment and the individual’s ability to cope with them. In this case, this might be a failing grade or peer competition.

Researchers have been able to prove that test-taking anxiety leads to an individual’s body beginning to hyperventilate, thereby producing a physiological reaction similar to that reaction induced by a threatening event [12]. As a conclusion, test anxiety provokes a clear alteration in physiological parameters.

2.5 Protocols

Data was collected for 25 minutes from 25 subjects. Every subject was made to read and sign the consent form according to the Institutional Review Board IRB. Every participant was instructed on the specific manner in which the answers should be recorded. The steps include:

- The subject was given three ECG electrodes to place close by the heart, one on the right side of the heart, the other on the left side, while the last electrode was placed below (about 5cm) the left electrode.
- ESD strap was placed on the subject’s hand.
- ECG connectors were then connected to the electrodes on the subject’s chest.
- The subject’s hand was swabbed with water to ensure a good connection for the GSR sensor.
- GSR sensor was connected to the index and middle finger of the left hand and the subject was instructed not to make any rough movement with that hand during the experiment.
After the data collection process, the data was stored in a computer for later analysis.

Figure 2.5 A volunteer during the experiment
After all the probes are placed, ECG data and GSR data are checked for accuracy (that is making sure all the waveforms are appropriate for the system), recording of data is then switched on.

For the first 5 minutes, the subject is made to listen to music (Vivaldi Four Seasons) on YouTube in order to measure the baseline for a non-stressed condition. The next 5 minutes, the subject takes the Montreal Imaging Stress Task MIST [4] which is a mathematics test which comprises addition, subtraction, multiplication, and division. See the Fig. 2.7 and 2.8 below.

![Figure 2.7 Sample of the Montreal Imaging Stress Task](http://wonderlictestsample.com/50-question-wonderlic-test/)

![Figure 2.8 Wonderlic Test](http://wonderlictestsample.com/50-question-wonderlic-test/)

After the MIST, the subject takes the Wonderlic Test WT [4] which is used by many employers and educational facilities to assess their candidates. The test consists of mathematical questions, English questions, and general knowledge questions. The subject answers 50 questions in 12 minutes and is graded according to the correctness of the questions answered. Finally, for the last 3 minutes, the subject continues to listen to music.
CHAPTER 3 TEMPLATE EXTRACTION

3.1 Identifying Stress During the Experiment

After a baseline has been achieved and recorded for both sensors, any extreme increment in the Heart Rate (HR) and subsequent decrement in GSR value simultaneously when taking the test is considered as a stressed state. Take, for example, an athletic subject who has an ECG average baseline of 55bpm to 65bpm and a GSR value of 435 Siemens to 450 Siemens, during rest. If a HR of 80bpm to 85bpm and a GSR value of 370 Siemens to 395 Siemens is recorded simultaneously, that subject is undergoing some form of physiological stress.

3.2 Template/Tagging Extraction

Combining both the physiological signals and the different non-stressing and stressing task explains how the template is created. The template extraction is required so that the system can create a profile in order to contrast whether a subject is actually undergoing stress or not. This template is based on specific characteristics extracted from a subject with respect to parameters from the physiological signals HR and GSR.

Since the different states of stressed and non-stressed cannot be controlled by an individual, the system must know how both signals behave in both situations. The first step consists of extracting a relaxed template from the user, this template shows the behavior of the GSR and HR data in the relaxed state, the second step consists of extracting the stressed state from the user and these templates shows the behavior of the data in the stressed state. Finally, the third state comprises getting the relaxed state of the subject after all the stressors have been applied. The final state regards the fact that after a stressor, HR and GSR require more time to achieve a calm state. Therefore, the first and third state diverge in terms of HR and GSR despite the fact that the subject is doing the same task [12].

In a non-stressed state, the HR of a human ranges from 40 – 60bpm for an athletic person and from 80 – 100bpm for a regular individual [13]. The GSR values for humans are affected by a range of factors, so there is no concrete range of value for a human. Instead, what is important is the trend of data changes [10]. Once a baseline value for both HR and GSR are achieved, the system is modelled to pick a value of 10 – 15 bpm above the baseline value for HR data, and a value of 40 – 50 Siemens below the baseline value for the GSR data (simultaneously) and categorize it as a stressed state, thereby making the model specific to individuals. Below is an image showing how the template was made.
As can be seen from the image, specific points corresponding to the various stressors are picked up by the model and these points fall basically when the stressor is active.
CHAPTER 4 CLASSIFICATION TECHNIQUES

4.1 Stress Detection Using Scientific Approaches

After the template for the stressed and non-stressed states have been extracted, this section describes how the algorithm and classifier are used for stress detection.

4.2 Linear Discriminant Analysis (LDA)

The LDA method is a generalization of Fisher’s linear discriminant and is used in statistics, pattern recognition, and machine learning to find a linear combination of features that characterizes two or more classes of events [14]. The result may be used as a linear classifier or dimensionality reduction (which is what is used in this case). A hyperplane in the p-dimensional attribute space is used to separate the known classes, points are then classified according to what side they fall on in the hyperplane. The Linear discriminant analysis was defined for the case of two classes by letting $x, x_1, x_2$ be the respective means of attribute vectors over the two classes, with a coefficient set $a_1...a_p$. Consider a set of observations (also called features, attributes, variables or measurements) for each sample of an object or event with known class [14]. This set of samples is called the training set. The classification problem is then to find a good predictor for the class of any sample of the same distribution (not necessarily from the training set) given only an observation [14]. The between-class to within-class variance is the Fisher ratio used. A picture of the LDA of the data can be seen in the appendix under individual results. Also, lines 67 to 72 in the appendix shows how the LDA features are selected. Lines 90 through 114 shows the linear algorithm selecting the training data and putting it into class.
4.3 Support Vector Machine (SVM)

Support vector machines are supervised learning models used for classification and regression analysis [8]. SVM classifiers are used to predict future trends. The main idea of SVM is to find an optimal hyperplane that maximizes the margin between two groups of samples. In using the SVM classifier, two steps were used: some part of the data are selected randomly and trained as the SVM classifier and in the second step, the trained data is used to classify the rest of the data. 5000 samples of the data are selected randomly for testing and another 5000 for training. The appendix provides the code used for classifying the data using SVM. After the samples have be
placed into training and testing (lines 53 to 70), these samples are then classified in lines 73 through 80.

### 4.4 Multilayer Perceptron (MLP)

Multilayer perceptron is a class of feedforward artificial neural networks [18]. It consists of at least three layers of nodes (input, hidden layers, and output), and except for the input node, each node is a neuron that uses a nonlinear activation function [7]. MLP utilizes a supervised learning technique called backpropagation for training [7]. The appendix shows the code used for classifying the data using MLP, after the samples have been placed into training and testing (lines 53 to 70) these samples are then classified in line 81 through 88.

![Multilayer Perceptron showing the different layers](image)

*Figure 4.2 Multilayer Perceptron showing the different layers*
CHAPTER 5 RESULTS

5.1 Results

A stress detection system must reach a compromise between detecting properly which individuals are under stress situations, and which individuals are in a relaxed state [1]. Two assessment parameters are used. True Stress Detection (TSD) is when the system properly detects stress when an individual is under stress stimuli. It is modeled as:

\[ TSD = \frac{TP}{TP+FN} \]

where a true positive means classifying as stressed an individual which is stressed, and a false negative means classifying as relaxed an individual which is under stressing situations.

True Non-Stress Detection rate (TNSD) is when the system correctly detects no stress in an individual and the subject is not under stressing situations. TNSD is modeled as:

\[ TNSD = \frac{TN}{TN+FP} \]

where a true negative means classifying as non-stressed as an individual which is not under stress, and false positive means classifying as stressed an individual which is relaxed. The table below shows the results from all 25 people.

| Subject | TSD for MLP | TNSD for MLP | TSD for SVM | TNSD for SVM |
|---------|-------------|--------------|-------------|--------------|
| 1       | 89.9        | 100          | 87.8        | 100          |
| 2       | 85.75       | 100          | 84.97       | 100          |
| 3       | 88.39       | 100          | 84.36       | 100          |
| 4       | 85.84       | 100          | 85.82       | 100          |
| 5       | 86.95       | 100          | 82.95       | 100          |
| 6       | 85.3        | 100          | 80.24       | 100          |
| 7       | 87.46       | 100          | 86.25       | 100          |
| 8       | 90.05       | 100          | 88.98       | 100          |
| 9       | 87.8        | 100          | 88.67       | 100          |
| 10      | 92.23       | 100          | 91.78       | 100          |
| 11      | 89.74       | 100          | 87.34       | 100          |
| 12      | 86.56       | 100          | 86.32       | 100          |
| 13      | 90.75       | 100          | 90.45       | 100          |
| 14      | 91.32       | 100          | 89.61       | 100          |
| 15      | 88.98       | 100          | 88.35       | 100          |
| 16      | 89.0        | 100          | 89.34       | 100          |
| 17      | 87.64       | 100          | 86.45       | 100          |
| 18      | 85.01       | 100          | 86.32       | 100          |
|   |      |      |      |      |
|---|------|------|------|------|
| 19| 88.65| 100  | 87.44| 100  |
| 20| 86.89| 100  | 86.7 | 100  |
| 21| 89.45| 100  | 88.75| 100  |
| 22| 88.78| 100  | 88.6 | 100  |
| 23| 87.65| 100  | 87.65| 100  |
| 24| 92.57| 100  | 91.88| 100  |
| 25| 89.32| 100  | 89.45| 100  |
CHAPTER 6 FUTURE WORK

6.1 How to Improve the System

Both sensors used are off-the-shelf and made commercially with no care of precision. In other words, both sensors are relatively noisy and sometimes do not produce a signal on the hardware end that is sufficient for reliable analyses. The manufacturers only fix the issue of noise on the software end, so it looks good on the interface. When such data is saved for further usage, a lot of filtering and noise cancellation techniques are needed to achieve a reasonable Signal to Noise Ratio (SNR). To improve the SNR, one needs to reduce the noise (from the sensor) software and hardware. It is beneficial to design and build the sensor for its specific use, taking into account the performance and reliability required for the use. A simple way to improve the ECG sensor is to ensure a high-quality instrumentation amplifier is used. A good quality instrumentation amplifier will reduce majority of the noise due to impedance matching. At the software end, a lowpass filter will greatly improve the SNR for the ECG sensor.

A third sensor will improve the accuracy of the measurement. An accelerometer will serve as a good measure of position for the person experiencing stress. During stressful conditions, humans often fidget or move parts of their body in an awkward manner [16], and a 3-axis accelerometer will serve as a good sensor to measure such movements which can be classified at a later time [11].

The GSR sensor has a better signal-to-noise ratio when compared to the ECG sensor. With respect to reliability, both sensors are equally reliable: the GSR sensor will easily pick up a change emotion (sad, happy, nervous, angry, tired), and the same is true for the ECG sensor because they both are based on the sympathetic nervous system. Neither out performs the other, they both work hand-in-hand to increase the reliability and accuracy. With one of these sensors working by itself, the accuracy with respect to measurements will be lower.

Other techniques can be used to analyze the data so as to improve the accuracy of the measurement. Techniques such as $k$ Nearest Neighbor, fuzzy logic and regression are useful.

6.2 Conclusion

As mentioned in the synopsis, the main objective of this thesis is to investigate the efficacy of the fusion of data from off-the-shelf sensors to accurately determine stress in humans. Several techniques were used to solve this problem (linear discriminant analysis, support vector machine and multilayer perceptron). The multilayer perceptron gave the best accuracy when classifying both data.

The results shown from both sensors validate the fact that HRV and GSR are important methods in measuring stress and an inclusion of a third sensor (accelerometer) will improve the overall
accuracy of the measurements. Also, other techniques can be used to classify the data, possibly improving the accuracy.
### APPENDIX A

#### Code

//This code is to read in the already stored ECG data from the computer, plot the filtered and unfiltered ECG data and set the ECG data in seconds.

```matlab
1- function [gsr_ecg] = 
    textRead(txtFile,ascFile,networkFreq,ecgSampleFreq)

2- ecg = load(txtFile);
3- ecg(:,1) = ecg(:,1) - floor(ecg(1));
4- q(:,1)=ecg(:,3);
5- ecg(:,3) = notch(ecg(:,3),ecgSampleFreq,networkFreq);
6- q(:,2)=ecg(:,3);
7- ecg(:,3) = FIReq(ecg(:,3),ecgSampleFreq,100,100);
8- q(:,3)=ecg(:,3);
9- figure,plot(q),legend('Original','Notch filter','EQ Filter')
10- figure,subplot(2,1,1),plot(q(:,1)),title('Original ECG'),subplot(2,1,2),plot(q(:,3)),title('Filtered ECG')

11- sEc = unique(ecg(:,1));
12- for k = 2:length(sEc)
13-     dc = sEc(k) == ecg(:,1);
14-     dc1 = sum(dc);
15-     ecg(dc,1) = ecg(dc,1) + (0:1/dc1:1-1/dc1)';
16- end
17- figure,plot(ecg(:,1),q),legend('Original','Notch filter','EQ Filter')
18- figure,subplot(2,1,1),plot(ecg(:,1),q(:,1)),title('Original ECG'),subplot(2,1,2),plot(ecg(:,1),q(:,3)),title('Filtered ECG')
19- D = readAsc(ascFile);
20- sEc = unique(floor(D(:,1)));
21- for k = find(D(:,1)==sEc(2),1,'first'):find(D(:,1)==sEc(end),1,'first')
22-     [~,p] = min(abs(D(k,1) - ecg(:,1)));
23-     gsr_ecg(k,:) = [D(k,2) ecg(p,3) D(k,1) ecg(p,2) ecg(p,4)];
24- end
25- figure,subplot(4,1,1),plot(gsr_ecg(:,3),gsr_ecg(:,4)),title('PQRS T waveform'),axis tight
26- subplot(4,1,2),plot(gsr_ecg(:,3),gsr_ecg(:,2)),title('real time HRV'),ylabel('bpm'),axis tight
27- subplot(4,1,3),plot(gsr_ecg(:,3),gsr_ecg(:,5)),title('avaged HRV'),ylabel('bpm'),axis tight
28- subplot(4,1,4),plot(gsr_ecg(:,3),gsr_ecg(:,1)),title('GSR'),xlabel('Seconds'),ylabel('Siemens'),axis tight
29- gsr_ecg = gsr_ecg(:,1:3);
30- end
```
32. Reading the already stored GSR data

```matlab
function [D] = readAsc(filename);

fid = fopen(filename);
k = 0;
while ~feof(fid)
l = fgetl(fid);
if length(l)==0, continue, end
k = k + 1;
dc1 = strfind(l, ':');
D(k,:) = [str2num(l(dc1(end-4)) - str2num(l(dc1(end-1)-(2:-1:1))) str2num(l(dc1(end)-(2:-1:1))) str2num(l(dc1(end)+(1:2))) - str2num(l(dc1(end)+4:end))];
end
D(:,1) = (D(:,1)~= D(1))*24*3600 + (D(:,2) - D(1,2))*3600 + (D(:,3) - D(1,3))*60 + D(:,4) - D(1,4);
D(:,2:4) = [];
end
sEc = unique(D(:,1));
for k = 2:length(sEc)
dc = sEc(k) == D(:,1);
dc1 = sum(dc);
D(dc,1) = D(dc,1) + (0:1/dc1:1 - dc1)';
end
fclose(fid);
end
```

53. function [TSD,TNSD,Precision,Recall,Accuracy] = LDAnn(Xtrain,TrainLabel,Xtest,TestLabel);

% the two columns of Xtrain and Xtest represent the training data
and the % testung data, each row is a sample
% TrainLabel and TestLabel are the labels for the training data
and for the % testing data - the length of the TrainLabel equals to the number
% of rows in
% the training data

59. %normalizing the data
ts = size(Xtrain,1);te = size(Xtest,1);
M1 = max(Xtrain(:,1));
M2 = max(Xtrain(:,2));
m1 = min(Xtrain(:,1));
m2 = min(Xtrain(:,2));
Xtrain = (Xtrain - ones(ts,1)*[m1 m2])./(ones(ts,1)*[M1-m1 M2-m2]);
Xtest = (Xtest - ones(te,1)*[m1 m2])./(ones(te,1)*[M1-m1 M2-m2]);
%feature selection
\[
[Y\text{train}, W] = \text{LDA}(X\text{train}, \text{TrainLabel}, 1); \\
Y\text{test} = \text{LDA}(X\text{test}, W, 0); \\
Y = [Y\text{train}; Y\text{test}]; \\
\text{figure, scatter}(Y(~[\text{TrainLabel}; \text{TestLabel}], 1), Y(~[\text{TrainLabel}; \text{TestLabel}], 2), 17, 'b'), \text{title('Scatter plot of the two LDA components')}, \text{hold on} \\
\text{scatter}(Y([\text{TrainLabel}; \text{TestLabel}], 1), Y([\text{TrainLabel}; \text{TestLabel}], 2), 2, 'r'), \text{legend('Not Stressed', 'Stressed')}, \text{hold off}
\]

\%Classification
\%SVM and MLP Classification
SVMStructure = \text{svmtrain}(Y\text{train}, \text{TrainLabel});
Results = \text{svmclassify}(\text{SVMStructure}, Y\text{test});
\[\text{TSD}, \text{TNSD}, \text{Precision}, \text{Recall}, \text{Accuracy} = \text{calculateMeasurements}(\text{Results}, \text{TestLabel});\]
\text{display(strcat('For SVM classification TSD='})
\text{display(strcat('For SVM classification Precision='})
\text{display(strcat('For SVM classification Accuracy='})
\text{mlp} = \text{feedforwardnet}([5 5]);
\text{mlp.trainParam.showWindow} = \text{false};
\text{mlp} = \text{train}(\text{mlp}, X\text{train}', \text{TrainLabel}');
\text{ResultsMLP} = \text{logical}(\text{round}(\text{mlp}(X\text{test}')));
\[\text{TSDmlp}, \text{TNSDmlp}, \text{Precisionmlp}, \text{Recallmlp}, \text{Accuracymlp} = \text{calculateMeasurements}(\text{ResultsMLP}, \text{TestLabel});\]
\text{display(strcat('For MLP classification TSD='})
\text{display(strcat('For MLP classification Precision='})
\text{display(strcat('For MLP classification Accuracy='})
\text{end}

\%Using LDA algorithm
\text{function} \ [Y, W] = \text{LDA}(X, W, \text{train});
\text{if} \ \text{train} == 1 \\
\text{M} = \text{mean}(X); \\
\text{theClases} = \text{unique}(W); \\
\text{C} = \text{length}(\text{theClases}); \\
\text{Sb} = \text{zeros}(C); \\
\text{Sw} = \text{zeros}(C); \\
\text{for} \ c = 1:C \\
\text{bin} = \text{theClases}(c) == W; \\
\text{x} = X(\text{bin}, :); \\
\text{Mi} = \text{mean}(X(\text{bin}, :)); \\
\text{m} = \text{Mi} - \text{M}; \\
\text{Sb} = \text{Sb} + (\text{m}'*\text{m}); \\
\text{Sw} = \text{zeros}(C);
Ni = size(x, 1);
for k = 1: Ni
m = x(k, :) - M;
Swi = Swi + (m' * m);
end
Sw = Sw + Swi / Ni;
end
[W, ~] = eig((Sw^(-1)) * Sb);
end

Y = X * W;

% Getting the TSD, Precision, Recall, Accuracy and TNSD from the data
function [TSD, TNSD, Precision, Recall, Accuracy] = calculateMeasurements(Results, TestLabel);

TrueNegatives = 0; TruePositives = 0;
FalseNegatives = 0; FalsePositives = 0;
for k = 1: size(Results, 1)
if Results(k) == TestLabel(k)
if Results(k) == 1
TrueNegatives = TrueNegatives + 1;
else
TruePositives = TruePositives + 1;
end
else
if Results(k) == 1
FalseNegatives = FalseNegatives + 1;
else
FalsePositives = FalsePositives + 1;
end
end
TSD = 100 * TruePositives / (TruePositives + FalseNegatives);
TNSD = 100 * TrueNegatives / (TrueNegatives + FalsePositives);
Precision = 100 * TruePositives / (FalsePositives + TruePositives);
Recall = 100 * TruePositives / (FalseNegatives + TruePositives);
Accuracy = 100 * (TruePositives + TrueNegatives) / (TruePositives + TrueNegatives + FalseNegatives + FalsePositives);
end

Labelling
function [Xtrain, TrainLabel, Xtest, TestLabel] = labelingData(X, gsrThreshold, ecgThreshold, TrainSetPercentage);

stressLabels = (X(:, 1) > gsrThreshold) & (X(:, 2) > ecgThreshold);
tsn = round(size(X, 1) * TrainSetPercentage / 100);
if sum(stressLabels(1:tsn) == 0) == 0, display('Not enough "No stress" samples in the training set'), return, end
if sum(stressLabels(1:tsn)==1) == 0, display('Not enough "Stress" samples in the training set'), return, end

if sum(stressLabels(tsn+1:end)==0) == 0, display('Not enough "No stress" samples in the testing set'), return, end

if sum(stressLabels(tsn+1:end)==1) == 0, display('Not enough "Stress" samples in the testing set'), return, end

Xtrain = X(1:tsn,1:2);
TrainLabel = stressLabels(1:tsn);
Xtest = X(tsn+1:end,1:2);
TestLabel = stressLabels(tsn+1:end);

display (strcat('Training set: number of no stress samples=',num2str(sum(TrainLabel == 0)),' and number of stress samples=',num2str(sum(TrainLabel))));
display (strcat('Testing set: number of no stress samples=',num2str(sum(TestLabel == 0)),' and number of stress samples=',num2str(sum(TestLabel))));

figure,plot(X(:,3),stressLabels*2*max([X(:,1);X(:,2)])-1,:k'),axis tight,ylim([0 max([X(:,1);X(:,2)])]),hold on
plot(X(:,3),X(:,2),'-r')
plot(X(:,3),X(:,1),'-b'),legend('Stressed','Heart Rate (BPM)','GSR (µOhm^-1)'),xlabel('Time (s)'),hold off

figure,scatter(X(~stressLabels,2),X(~stressLabels,1),17,'b'),xlabel('Heart Rate (BPM)'),ylabel('Galvanic Skin Response (µOhm^-1)')
axis manual,hold on,scatter(X(stressLabels,2),X(stressLabels,1),27,'r'),legend('Not Stressed','Stressed'),hold off;

end

Filtering
function Y = FIReq(X,Fs,Fp,N);

Rp  = 0.00057565; % Corresponds to 0.01 dB peak-to-peak ripple
Rst = 1e-4; % Corresponds to 80 dB stopband attenuation
b = firceqrip(N,Fp/(Fs/2),[ Rp Rst]);
Y = filter(b,1,X);
end

function Y = notch(X,Fs,Fn);

w0 = Fn/(Fs/2);
bw = w0/35;
[b,a] = iirnotch(w0,bw);
Y = filter(b,a,X);
end
APPENDIX B

Consent Form

Study

The study of this research is about creating and measuring stress in humans using electrocardiogram (ECG) and Galvanic skin response (GSR). Probes from the ECG and GSR sensor will be connected to your body in order to take data.

Task

You will be instructed to listen to music (Four Seasons by Vivaldi) for 5 minutes, after which you will be giving a game that contains simple mathematical calculations to play. The game will be timed and you will be graded based on your performance.

Risk

The only risk involved is peeling of any hair on the chest as a result of the ECG probe connected to your chest. If you do not have hair on your chest, there is no risk involved.

Taking part in this research is voluntary and will not affect any relationship with the University of Arizona and your data will be marked confidential with your name not disclosed with anyone in the University.

If you have questions please reach out to the researchers Odafe Jeroh and Dr. Linda Powers on ojeroh@email.arizona.edu and lsp@email.arizona.edu. A copy of this form will be given to you to keep for your own personal records.

Statement of Consent: I have read the above information, and have received answers to any questions I asked. I consent to take part in the study.

Your Signature ___________________________ Date __________________________

Your Name (Printed)
__________________________________________________________________________

This consent will be kept by the researcher for at least three years beyond the end of the study.
APPENDIX C

Individual Results for all Subjects

Graphs of the all the data for each of the 25 subjects are shown below. The baseline was chosen approximately around 150 – 200 seconds from the start of the experiment for every subject. You will notice that about 5 minutes or 300 seconds into the experiment, every subject experienced some form of stress due to the MIST stressor, and those stress levels continued for the most part in all subjects while undergoing both stressors. Finally, the last 180 seconds shows the subject relaxing from every stressor.
Subject 1

This subject had a regular HRV (80-100bpm) and a steady GSR value in the relaxed state but when the stressors kicked in, the HRV went up and the GSR value went down as expected for the subject. Below are pictures of the subject data collected.
Scatter plot of the two LDA components

- Not Stressed
- Stressed
Subject 2

This is an athletic subject with HRV ranging from 40 – 60 bpm, the subjects GSR value was constant during the relaxed state of the experiment (within ±7 siemens of the initial value). When the stressors became effective, the values of the HRV and GSR both went up and down simultaneously as can be seen from the graphs. After the stressors were taken out, you can see from the third image that the values from both sensors stabilized to a rest condition.
Subject 3

This subject had an average HRV value of approximately 75 bpm during the relaxed stage and a change of ±5 siemens for the GSR value. Both sensors data followed the trend of increasing for ECG and decreasing for GSR when the stressors became effective. These observations can be seen from all 4 images shown below.
Subject 4

The baseline (HRV) for this subject fall in the athletic category. Two minutes into the experiment, the subject started feeling nervous (although it did not record as a stress condition because it did not reach the limits for HRV and GSR value picked for this subject). The stressor also had a similar effect on this subject as it did to others. On seeing the result from the final stressor, the subject felt sad and you can see this trend around the 22\textsuperscript{nd} to 23\textsuperscript{rd} minute mark.
Scatter plot of the two LDA components

- Not Stressed
- Stressed
Subject 5

The baseline for this subject's HRV was chosen at approximately 65 bpm and the GSR value was approximately ±4 siemens during the baseline selection. The MIST and Wonderlic test started extremely hard for this subject and had similar effects on the subject.
Scatter plot of the two LDA components

Not Stressed
Stressed
Subject 6

This subject falls under the athletic category for HRV and a baseline of 54 bpm was used. The GSR data had a value of ±5 siemens during the baseline. The stressor had a similar effect on this subject but after 8 minutes into the experiment, the subject figured that if you wait a bit, the stressor changes to an easier question. This subject was not happy with his result.
Subject 7

This subject’s baseline was marked at approximately 75 bpm for HRV and the GSR had a ±3 siemens during the baseline selection. About a minute into my data collection from this subject, the subject was startled when I tried to take a picture (you can see this on the 3rd image). Both stressors had similar effect on this subject.
Subject 8

This subject was worried when the music was played for him to relaxed-and the subject kept on voicing out his opinion. A baseline of approximately 78 bpm was used for this subject. The stressors had similar stressing-effect on him as did other subjects.
Subject 9

This subject’s baseline for HRV was selected at approximately 79bpm and the GSR value had a difference of ±4. The stressor had a similar effect on this subject.
Scatter plot of the two LDA components

- Not Stressed
- Stressed
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