DETERMINATION OF EMOTIONAL STATE THROUGH PHYSIOLOGICAL MEASUREMENT

by

Lee B. Hinkle, B.S.

A thesis submitted to the Graduate Council of
Texas State University in partial fulfillment
of the requirements for the degree of
Master of Science
with a Major in Computer Science
December 2016

Committee Members:

Vangelis Metsis, Chair

Mina Guirguis

Yijuan Lu

FAIR USE AND AUTHOR'S PERMISSION STATEMENT

Fair Use

Duplication Permission

DEDICATION

To the memory of my mother and father, Irene M. and Glenber L. Hinkle who consistently stressed the importance of education and helping others.

ACKNOWLEDGEMENTS

One of my favorite metaphors is “we stand on the shoulders of giants”. The work presented here is the result of the efforts of many people who have generously shared their knowledge and support with me directly and indirectly. As I sit here writing on a Friday night I am reminded that the research and discovery is the fun part but real value comes from documenting the information so it can be used by others. I am particularly grateful to those who teach and share their knowledge broadly.

I want to thank my advisor Dr. Vangelis Metsis for establishing the Intelligent Multimodal Computing and Sensing lab which I am proud to be a part of as both student and a researcher. I am grateful for his guidance on deeply technical topics as well as presentations and papers. My fellow researcher and frequent lunch buddy Kamrad Roudposhti was always willing to help me with MATLAB and machine learning principles. I learned a great deal during our frequent brain storming sessions at the whiteboard. I would like to thank a full cast of fellow researchers and students with whom I have enjoyed spirited discussions and in some cases collaborated with on graduate projects: Alakh Biniwale, Sahar Azimi, Jayadharini Jaiganesh, Justin May, Xiaoqing Liao, Iaonnis Rigas, Priyank Trivedi, Adam Anderson, Thomas Hsiao.

I would like to thank Dr. Yijuan Lu and Dr. Mina Guirguis for agreeing to serve on my committee. Molly O’Neil generously provided me with many great pointers and bits of advice and also serves as an inspiration through the care she shows for her

students and the effort she puts into teaching. Susan Alexander helped me immensely with the purchasing and receipt of equipment, many times from non-traditional suppliers. Shannon Hicks was always helpful when I really didn't know who else to ask.

I would like to thank Texas State University for offering options for those of us working in industry to continue our education at the Graduate Level. The Support Grant Fellowship awarded to me by the Graduate College was critical for the purchase of the virtual reality and recording equipment and is very much appreciated. I am hopeful that this equipment will serve the needs of future Computer Science students for many years.

I would like to thank Dr. Kenneth Smith for the use of the Virtual Reality Lab and David Morely for helping me with some of the early and very critical VR runs.

Although we have only met via email I would like to thank Bernard Tarver at Great Lakes Neurotechnologies for his prompt and patient replies to my frequent questions regarding the BioRadio.

Finally, I would like to thank my wife Christine for her support while returned to full time student status and focused on my studies and research. I would also like to thank my wonderful daughters; Paige lent me the original Oculus DK2 while Shawn shared her MATLAB experiences and opinions.

TABLE OF CONTENTS

Page

LIST OF TABLES

Table **Page**

LIST OF FIGURES

Figure **Page**

LIST OF ABBREVIATIONS

Abbreviation	Description
Ag/AgCl	Silver/Silver Chloride
CSV	Comma Separated Value
ECG	Electrocardiogram
EDA	Electrodermal Activity
EEG	Electroencephalogram
EMG	Electromyography
EOG	Electrooculography
GSR	Galvanic Skin Response
HRV	Heart Rate Variability
kNN	k-th Nearest Neighbor
PPG	Photoplethysmogram
PPV	Pulse Pressure Variation
PulseOx	Pulse Oximetry
RIP	Respiratory Inductance Plethysmography
SKT	Skin Temperature
SpO2	Oxygen saturation of arterial hemoglobin
SVM	Support Vector Machine

ABSTRACT

The goal of this thesis is to develop and evaluate methods of emotional response classification using human physiological data. With the continued development of automated systems that interact closely with humans in a more natural manner the ability of such systems to determine the emotional state of nearby subjects and adapt accordingly is increasingly important. Applications include the broad area of affective computing as well as more specific areas such as evaluating the effectiveness of virtual reality based treatment for social phobias. In this work, various non-invasive sensors are used to collect physiological data during virtual reality simulations. Feature extraction, feature selection, and machine learning is performed on the data to determine which signals and algorithms produce the most accurate classification of the subject's emotional response to the simulations.

1 INTRODUCTION

The primary goal of this research is to determine emotional state through the non-invasive collection and analysis of physiological data during virtual reality or other immersive audio/visual simulations. Physiological data is data pertaining to biological systems. Physiological signals, also known as biosignals, such as the appearance of the skin, the mechanical response to light tapping, and acoustic data such as heart, breathe, and gastrointestinal sounds have been collected and used to assess overall health for many centuries [1]. Humans have the ability to determine if a person is upset or ill based on observation and experience without formal medical training. Pale skin, sluggish movement, and raspy voice are all common clues that a person might be ill. Similarly, we are able to detect if a person is upset, happy, or sad by observing physical clues, actions, and environmental factors. Humans however are not able to directly measure the electrical potentials that exist on and within the body. As we think and move our bodies develop electrical potentials that can be measured. With current technology we have the ability to measure very small signal electrical differences through the use of non-invasive adhesive sensors connected to very sensitive amplifiers. The data collected can be processed using digital signal processing and machine learning classification algorithms to perform meaningful work such as sleep analysis and disease diagnosis.

Continued technological advancements combined with existing and new needs is driving significant work in the field of human computer interaction. One the technical side the incredible growth in smartphones has not only provided easy access to data acquisition at almost any time it has also brought about a significant increase in

performance while lowering of cost of many sensors. Cameras, ambient light detectors, and accelerometer/gyroscope combination sensors have all benefited significantly due to the popularity of smartphones. When incorporated into a smartphone or wearable device these sensors can provide significant information about the owner's activities and the environment surrounding them. Additionally, significant improvements in processing power due to the availability of cloud based computing and massively parallel graphical processing units allow us to run much more sophisticated and computationally complex algorithms on ever increasing amounts of collected sensor data.

This research will be applicable to many real-world problems including: the evaluation of the effectiveness of various addiction treatments, the study of the impact of media and/or audio/visual stimuli such as gaming, and the ability to monitor emergency responders during crisis simulations.

1.1 Motivation

There are multiple technological and demographic changes that highlight the need for evermore human aware computing. As more automated systems replace roles previously performed by humans it will be beneficial to provide the systems with some level of simulated empathy. This ability to adapt based on human emotion has been termed Affective Computing by Rosalind Picard [2]. The driverless car is an appropriate and familiar example of an emerging computing category that will benefit from additional information regarding the passengers and bystanders emotional state. Another example is home health devices and even robotic assistants where natural language interfaces can lower the barrier and obvious divide between human and computer.

Today many facilities are outfitted with emergency defibrillators which upon removal from the storage container provide spoken instructions on how to properly connect to the person requiring assistance. Once connected data sensor will be used to control the actions of the defibrillator or provide further vocal instructions. Lowering the barrier and facilitating more natural interaction between humans and the device will clearly improve the outcome in what is likely a life-or-death situation.

1.2 Challenges

In the following sections greater depth and detail will be provided on some of the challenges that can lead to poor prediction of emotional response. One of, if not the, key challenges is the obtainment of accurate measurements. There are a number of aspects that need to be considered. Some are inherent in the biology of the subjects; these include the fact that the signals themselves are very small and the body generates a variety of different electrical potentials in response to brain activity, muscle activity, and involuntary reactions to stimuli [3]. On the sensor side there is a constant struggle between the need for very good electrical conductivity to the skin and the non-invasive least intrusive goals for a system which would ideally be used continuously. For example, highly accurate measurement of muscle activity typically entails the use of a needle electrode in the muscle itself [4]. For the best non-invasive signal on the skin surface, skin preparation such as an alcohol scrub to remove dead cells and a strong adhesive electrode with pre-applied electrolyte gel is typically used. If the location has hair it may be shaved beforehand to facilitate a better connection and lessen the difficulty in removal of the electrode [5]. Given these hassles widespread adoption is unlikely.

However, it is easy to foresee that electrodes will be incorporated into clothing, jewelry, and other worn accessories. Currently the signals available through these types of sensors are far weaker and noisier than securely attached disposable electrodes [6]. Similarly, the results for replacing a gelled EEG electrode, one of the most cumbersome electrodes due to the quantity required along with hair interference for skin preparation are improving. [7]

This research is focused on the evaluation of current techniques from a technical perspective however, there are significant personal and privacy issues that will need to be addressed as data from sources such as webcams, wearable devices, and smartphones are used to give systems and their developers the ability to classify a person's emotional state. Stephen Fairclough provides a brief introduction to some of these considerations in his argument for stronger privacy protections of physiological data [8].

1.3 Applications

As machines become more human-like through emerging capabilities such as natural language recognition and response and they are used even more pervasively to complete tasks currently performed by humans such as home health care the importance of proper emotion state classification will increase [9]. For example, a taxi driver would be able to tell if a passenger appears uncomfortable and potentially nauseous. In that case the driver would likely take action such as providing fresh air, describing the current traffic situation and expected arrival time, or even modifying the route to limit the number of turns and curves. As self-driving cars replace this human task, it will be essential to have the capability to use the information regarding the passengers emotional

and physical well-being to perform the proper actions to ensure that their comfort is maximized and needs are met.

Despite many advances in sensor technologies, amplification techniques, filtering and machine learning algorithms the ability to predict emotional response is still quite low even with fairly cumbersome sensors, in controlled environments, and with limited classification labels [10]. However, the number of sensors worn or near a person will continue to increase significantly. Ultimately accurate prediction will likely require a significant amount of sensor fusion [11] with input not only from a number of sensors but also from a number of different types of sensors. With so many sensors techniques to eliminate noisy or erroneous data will have to be developed and improved so that a single bad sensor does not disrupt the accuracy of the entire system. Three broad categories of sensors are in use today to detect physiological data [12]. These include imaging via cameras, surface electrical sensors as described here, and the 6-axis accelerometer/gyroscope combination sensor [13] that is present in virtually every modern smartphone and tablet [14].

2 BACKGROUND AND RELATED WORK

Human observable physiological data plays and important role in many areas ranging from social interaction, parenting, and the practice of medicine. The discovery of the electrical nature of living organisms and improvements in the ability to measure very small signal electrical differences have enabled the collection of physiological data that is useful for sleep analysis [15] and disease diagnosis [16]. Early work regarding emotional states includes that by Ekman and Friesen on universal facial behaviors. This study used six emotional states: happiness, anger, sadness, disgust, surprise, and fear [17]. The interactions of the sympathetic and parasympathetic nervous system cause physiological changes that are measurable. Work in this area includes Emotion Classification based on Bio-Signals, [18] which measured electrodermal activity (skin resistance), electrocardiograph (heart activity), peripheral temperature, and blood oxygen levels. Image processing and machine learning techniques have been used to classify emption based on facial images and voice recordings [19].

From end to end the process of classification of human state followed by the research studies surveyed can be summarized as:

- Collect Data preferably utilizing multiple subjects who are experiencing a wide range of emotions.
- Process the data to remove noise and erroneous samples.
- Add labels with the emotional state information.
- Parse the data into fixed time segments e.g. 2.56 seconds for 50 Hz sampling yields 128 data points.

- Perform feature extraction on each data type and time segment e.g. the mean value and fundamental frequency.
- Separate the data into training and testing portions. Typically, the training data is significantly larger, a common split is 70% training, 30% testing.
- Use the training data to train the targeted classifier.
- Use the trained classifier to predict the emotional state of the testing data samples.
- Compare the predicted and actual results to establish the accuracy of the predictions. Actual versus predicted results are shown in a confusion matrix from which an overall accuracy and error rate can be computed.

2.1 Human Emotional Response

The prediction of human emotional response via biosignals is based on the relationship between the parasympathetic and sympathetic branches of the autonomic nervous system [20] [21] [22] [23]. Further details of the signals used are provided in the following sections.

2.2 Physiological Signals

This research includes only physiological signals that can be measured non-invasively. Specifically, sensors which involved puncturing of the skin or contact with mucosal membranes (e.g. oral thermometer) were excluded when determining the signals to be monitored. The remaining signals can be separated into two distinct categories – electrical biosignals and physical biosignals. The electrical signals are monitored via adhesive electrodes connected to a highly sensitive amplifier. The physical signals are

monitored with a variety of sensors which sense some physical aspect of the subject such as movement or surface skin temperature.

2.2.1 Electrical Physiological Signals

Significant information can be gained through the collection of electrical physiological data. The most commonly accessed electrical physiological signals are summarized in Table 1 and include:

Electroencephalogram (EEG): An external measure of the activity occurring in the brain. EEG signals are categorized based on location of measurement and frequency. They are among the most difficult electrical signals to measure due to the low signal amplitude, the difficulty in securing electrodes through the hair and to the scalp, and the likelihood of other signals such as facial muscle movement induced EMG to overwhelm the EEG signal [24].

Electrocardiogram (ECG): A measure of the electrical activity driving the heart [25]. Typically measured as a differential signal across the heart with electrodes placed on both wrists or both shoulders with a ground reference on the elbow. For medical applications additional electrodes are typically placed at predefined locations on the chest; the resulting signals provide insight in the sequence of contractions of the heart.

Electrodermal Activity (EDA): Electrodermal activity is historically referred to as Galvanic Skin Resistance (GSR). It is commonly recognized as a key signal in lie detector equipment [26] that includes two electrodes strapped to the tips of two fingers on the same hand. The fundamental observation is that during periods of increased arousal the electrical conductance of the skin decreases especially when measured across the

palm of the hand or sole of the foot [27]. It is one of the earliest electrical physiological signals to be associated with changes in emotions.

Electromyography (EMG): A measure of the electrical potential between two points along a muscle which indicates the level of muscle activity. Due to the inherent electrical resistance of the skin surface EMG measurements have limitations over needle based electrodes but meet the non-invasive criteria. To detect emotion response EMG measurements are typically made on muscles that tense under stress such as the jaw and shoulder muscles [28].

Electrooculography (EOG): The eyeball exhibits a voltage potential from front to back. By analyzing signals obtained from electrodes placed above/below and left/right of the eye the position and movement of the eye can be calculated [29]. This is especially useful for sleep studies where eye movement cannot be determined visually. Because the eye is so closely coupled to our vision system which represents a significant portion of our brain factors such as speed of movement and duration of held gaze are likely more important to emotional state than the actual direction the subject is looking.

Table 1: Electrical Physiological Signal Names and Sensor Types

Signal Name	**Sensor Type**	**Sensor Location**	**Physiological Data**
Electroencephalogram (EEG)	Ag/AgCl electrode	Scalp	Brain Activity
Electrocardiogram (ECG)	Disposable electrode	Wrists or Chest	Heart Rate, Heart Rate Variability
Electrodermal Activity (EDA) aka GSR	Finger Electrode	Hand or Foot	Skin Resistance, Sweat Gland Activity
Electromyography (EMG)	Disposable electrode	Arms, Legs, Face	Muscle Activity
Electrooculography (EOG)	Ag/AgCl electrode	Face	Eye Movement, Position

2.2.1 Non-Electrical Physiological Signals

The common electrical signals described previously represent only a subset of the possible physiological measurements that can be made. Many wrist or waist-worn fitness trackers can accurately measure movement and therefore they are able determine the number of steps taken. Mechanical or digital thermometers are frequently used to measure body core temperature. A partial list of non-electrical physiological measurements is in Table 2. In the field of emotion recognition and classification image

processing and machine learning techniques can be used on images of a person's face to classify emotion. Similar techniques have been applied to voice.

Table 2: Non-Invasive Physiological Signal Names and Sensor Types (partial list)

Signal Name	**Sensor Type**	**Sensor Location**	**Physiological Data**
Photoplethysmogram (PPG)	Photoelectric Pulse Oximeter	Finger, Earlobe	Heartrate, Blood Oxygen Level
Respiration	Belt, Flow Sensor	Chest, Face	Respiration Rate, Volume
Pupil	Imaging	Near Eye	Pupil Dilation, Eye Movement
Position	Accelerometer, Gyroscope	Torso, Head, Limbs	Movement
Peripheral Temperature (SKT)	Thermistor	Hand	Skin Temperature

2.3 Emotional Classification Labels

As mentioned previously the goal of this research is to accurately determine a person's emotional state. It follows therefore that some standard and widely recognized set of emotional state labels should be used. Unfortunately, there is not general agreement on a single set of labels that can correctly and accurately reflect a person's range of emotions and categorize them completely.

There does seem to be general agreement that two broad indicators underpin emotional state classification. The first is a measure of arousal or overall physiological activity. Minimum arousal would be reflective of calm, relaxed, bored states while high arousal would indicate excitement or fear. The second attribute is valence which is a measure of positive versus negative emotion. For example, is a person is in a highly aroused state they might be experiencing extreme joy or extreme terror. This difference would be reflected in the value of the valence [30].

One measure of the difficulty for an emotional classification problem is the number of possible outcomes, specifically the number of distinct emotional states that are to be determined. A binary classifier might obtain 50% accuracy by selecting only a single output state given an input of random data. Similarly, a classifier with six potential outcomes would achieve an accuracy of only 16.7% by pure chance. Given the wide variably and lack of clear consensus in the industry the labels used in classification by the studies that reported results varies considerably. The classification labels are listed in Table 3.

2.4 Experimental Elicitation of Emotional Response

The generation of intense physiological responses spanning a range of emotions is a challenge. Ethical aspects and subject health must be taken into account when planning experiments. Some of the least upsetting stimuli include colors, music, and self-directed thought experiments e.g. “Imagine a time when you were very happy”. With such an experimental setup the degree to which the emotion is experienced and consequently the level of physiological response will be limited [31]. In order to elicit

stronger emotional responses different and likely more upsetting or deceitful techniques have been used. This type of experimental setup necessitates a careful and thorough review by an independent Institutional Review Board (IRB) to insure the protection of the research subjects.

One surveyed study [32] utilized the existing International affective picture system (IAPS) photoset which is available upon request and approval from the National Institute of Mental Health Center for Emotion and Attention at the University of Florida [33]. Several benefits of this photo set include its availability and broad usage and its well-developed classification and categorization of the images. In order to induce a range of emotions the photoset include images which may be disturbing and therefore careful experimental procedures must be followed to insure proper outcomes and protect the subjects.

Two related studies utilized video game techniques [34] [35]. Given the ubiquity of video games and simulated environments this experimental setup poses less risk with the tradeoff that the range of emotions may be reduced. Of particular note is that [34] utilized the expertise of three trained physiologists to perform the labeling of the subjects' emotions based on the game scenario and direct observation of the subject.

Other experimental techniques employed by the studies surveyed include film clips, a board game, startling noises, and music. Other possible methods of inducing an emotional response include placing the hand in ice water also known as the "cold pressor" test [36], public speaking, "floor drop" or other startling scenarios within VR environments.

A summary of the techniques used by the surveyed studies during experimentation is included in Table 3.

Table 3: Emotion Elicitation Techniques and States

Ref.	**Technique**	**Assessment**	**Emotional States (Labels)**
[32]	IAPS Photoset	Based on IAPS classification	Arousal and Valence
[18]	Film clips, a game, unexpected noise	Subject Self-Reporting	Joy, Sadness, Anger, Fear, Surprise, Neutral
[34]	Simulated (VR) Driving	Experienced Psychologists	Arousal and Valence + High Stress, Low Stress, Disappointment, Euphoria
[37]	Music from Existing Corpus	Subject Self-Reporting	Anger, Joy, Sadness, Pleasure
[35]	Video Game – NHL 2003 against Friend, Stranger, Computer	Self-Reporting plus Survey Questions	Boredom, Challenge, Excitement, Frustration, Fun
[38]	Film Fragments	Prior Classification of Film Fragments and Self-Reporting	Neutral, Positive, Mixed, Negative

2.5 Data Processing and Feature Extraction

Since the signals measured are very small the effect of noise must be mitigated. Electrical systems in the facilities where the data is collected usually operate at 50 or 60Hz and therefore a band pass or notch filter is typically employed to eliminate any noise inducted via the building wiring and resulting electromagnetic fields [39].

Many of the studies reviewed employed fairly standard feature extraction techniques that are applicable to time based signals. Typical features include the mean value, root mean squared (RMS) value, mean max amplitude, rise duration, and heart rate. Proper feature extraction is a key component of the process to insure good results and includes some amount of domain knowledge. For example, heart rate can increase for non-emotional reasons such as increased physical activity. It has been shown that heart rate variability – the difference in timing between adjacent beat has been shown to have some level of correlation to the level of arousal present [40].

There are a number of machine learning classifiers available [41]. The topic of machine learning and classifiers is extensive, only a brief overview will be provided here. In a typical case the classifier is provided with an array consisting of multiple columns which contain attributes that have a measured value or calculated feature and one column with the label for training sets [42]. For a classic home price prediction example attributes might be total square footage and number of bedrooms. In this example the label would be last selling price and this would also be the value to be predicted for new samples. Each row of the input matrix represents a sample. When the training data is input into the classifier it determines the best set of values to fit the provided labels. Three of the most popular machine learning classifiers are:

k-Nearest Neighbor – the predicted value is the most prevalent value among the k samples that are closest to the input value in multidimensional space [43].

Support Vector Machines – the multidimensional solution space is separated by hyperplanes that are determine based on the training data. The input data prediction is determined by its location relative to the hyperplane divided space [44].

Artificial Neural Networks – modeled after the human brain these classifiers are constructed of neuron like nodes which can take multiple inputs to determine a single output [45]. The output of each node is typically connected to multiple additional nodes.

The prediction accuracy when using electrical physiological signals and machine learning techniques is typically low especially in juxtaposition with some current successes in the areas of voice recognition, facial recognition, and spam filtering [46] [47].

3 METHODOLOGY

The general activities included in this research are: Eliciting Emotional Response and Data Collection, Data Processing, Labeling, and Feature Extraction, Feature Selection, Training and Validation of Multiple Classifiers, Evaluation Using New Subject Data. Additional detail on each of these steps is provided in the following sections.

3.1 Experimental Design for Elicitation of Response

The Virtual Reality sessions were chosen from applications available for the Oculus Rift [48] that were also compatible with the Oculus DK2 headset with the following general criteria:

- Readily available content – free on Oculus web store
- Range of relaxing to exciting, while avoiding disturbing or mature content
- Both passive (movies, demos) and active (games) subject involvement.

The targeted total time wearing the VR headset was slightly more than 60 minutes. Early experiments showed that after approximately 1 hour subjects began to tire of the VR environment. The final session was a game which could be terminated at any time based on the subject's fatigue and desired to continue. The total time required to describe and launch the application plus the recording of subject's responses after each session so the actual in VR time was significantly less. The total time required per subject was approximate 2 ½ hours. This included skin preparation and application of the adhesive electrodes, connection of the electrodes to the BioRadio, adjusting and donning the RIP bands, and mounting of both radios as well as removal of the equipment after the conclusion of the VR sessions.

Session 1: Introduction to Virtual Reality Movie/Demo

This is a short film/animation that introduces the 3D capabilities of the VR headset. It was selected at the first session in order to get the subject used to the Virtual Reality headset and provide time to verify that all the sensors were recording properly. It contains several short 3D movies and is in general neutral.

Session 2: The Rose and I Movie

A short animated VR film by Penrose Studios that made its World Premiere in the New Frontier section at the Sundance Film Festival 2016. It is largely relaxing and pleasant with one potentially startling event where the flower "coughs."

Session 3: Discovery VR Action Videos

The application contains a number of videos and the following two were selected:
Video 1 "Get Ready for the Drop" is a 360° Video of a Rollercoaster ride
Video 2 "Jump into the Unknown" is 360° Video of a Rope Pendulum Swing
As both the rollercoaster and the pendulum swing would be considered "thrill" rides these were chosen to represent more exciting segments. In addition, the pendulum swing contained scenes that would be unsettling to someone with a fear of heights.

Session 4: InCell Game

An interactive game where you ride along a tubular track and try to capture white and green objects while avoiding red obstacles. This application was chosen to represent

game play where concentration is required and positive and negative consequences could be observed.

Session 5: Lost Movie

The second 3D Virtual Reality movie which takes place in a dark forest with multiple startling events such as a bird swooping by. It was anticipated that this movie would score higher arousal marks than the previous Rose and I movie.

Session 6: Dream Deck

A 3D Virtual Reality demo including multiple short demos. The city scene, alien encounter, and dinosaur were specifically singled out for subject response with the intent of invoking emotions including fear (of heights), anxiety (non-human experience), and a frightening (charging dinosaur) emotions.

Session 7: Lucky's Tale Game

A 3D adventure game using 3rd person perspective in a VR environment. This was chosen as the final session that the subject might find enjoyable and interactive. The subjects were given the option of stopping at any time or continuing to finish a full game which took approximately 15 minutes. For all the game the hope is that some in-game event will elicit an emotional response that can be analyzed however given the variation in game play this is very difficult to guarantee and the timing can vary considerably.

3.2 Data Collection

3.2.1 Physiological Signals Measured

Data collection was limited to non-invasive techniques, which include disposable adhesive electrodes on the skin, wearable type sensors such as respiration straps, finger electrodes, ear clips, motion, and potentially optical imaging. The physiological data was measured using two BioRadio Wireless Physiology Monitor and associated peripherals from Great Lakes Neurotechnology. The BioRadio provides 4 differential inputs that can be configured for a variety of electrical biosignals and an additional expansion pod that can be used for temperature sensing and pulse oximetry. As described in the BioRadio User's Guide "The BioRadio is worn by the person and is designed for acquiring physiological signals from sensors attached on the body. Physiological signals are amplified, sampled, and digitized, which can be wirelessly transmitted to a computer Bluetooth receiver and/or recorded to onboard memory for post-analysis." More details can be found in the user manual which is available online. [49]. Respiration was measured using Inductive Interface Cables and Universal Adjustable Respiratory Inductive Effort (RIP) belts made by SleepSense (S.L.P. Inc). The RIP bands and Interface Module provide a voltage input to the BioRadio which varies based on the measure chest and abdomen volume. This technique has been shown to reliably measure respiration [50]. The finger based pulse oximeter used was Model 3012LP by Nonin Technologies. Pulse Oximetry utilizes two types of LEDs to measure the absorption of light within the finger or earlobe to determine pulse, SpO2, and peripheral blood volume [51].

Table 4: Physiological Signals Recorded

Radio	Signal	Location	Qty
H_Ch1	EEG f4	High right forehead	1
H_Ch2	EOG - Horizontal	Outside of eyes	1
H_Ch3	EOG - Vertical	Above and below right eye	1
H_Ch4	EMG – Zygomaticus “smile” muscle	Right cheek	1
H_int	Accel XYZ, Gyro XYZ	Rear of head	6
B_Ch1	GSR (Electrodermal Activity)	Right index & pointer finger	1
B_Ch2	ECG	Left and right wrists	1
B_Ch3	Chest Respiration (RIP)	Chest strap	1
B_Ch4	Abdomen Respiration (RIP)	Stomach strap	1
B_Aux	Peripheral Temperature	Right pinkie finger	1
B_Aux	Heart Rate via PulseOx	Right ring finger	1
B_Aux	Blood Volume (PPG) via PulseOx	Right ring finger	1
B_Aux	Blood Oxygen (SpO2) via PulseOx	Right ring finger	1
B_int	Accel XYZ, Gyro XYZ	Right waist	6

3.2.2 Skin Preparation and Electrode Placement

Each subject was provided with an instruction sheet guiding them in the skin preparation and electrode application. They were asked to clean the skin where the electrode will be attached with an alcohol swab to remove any oils, lotions, makeup, etc. as well as dead skin. They were specifically told that was not necessary to scrub vigorously. They were also instructed to take care particularly around the eyes and installed the under eye electrode down far enough to avoid the sensitive under eye skin.

After the alcohol was allowed to dry, the cloth electrodes were removed from the backing (it helps if the facilitator removes the electrode and hands it to the subject) and applied to the skin as shown below.

Wrist/Hands

1 Middle segment of right index finger, palm side

2 Middle segment of right pointer finger, palm side

3 Left wrist, palm side

4 Right wrist, palm side

5 Right elbow

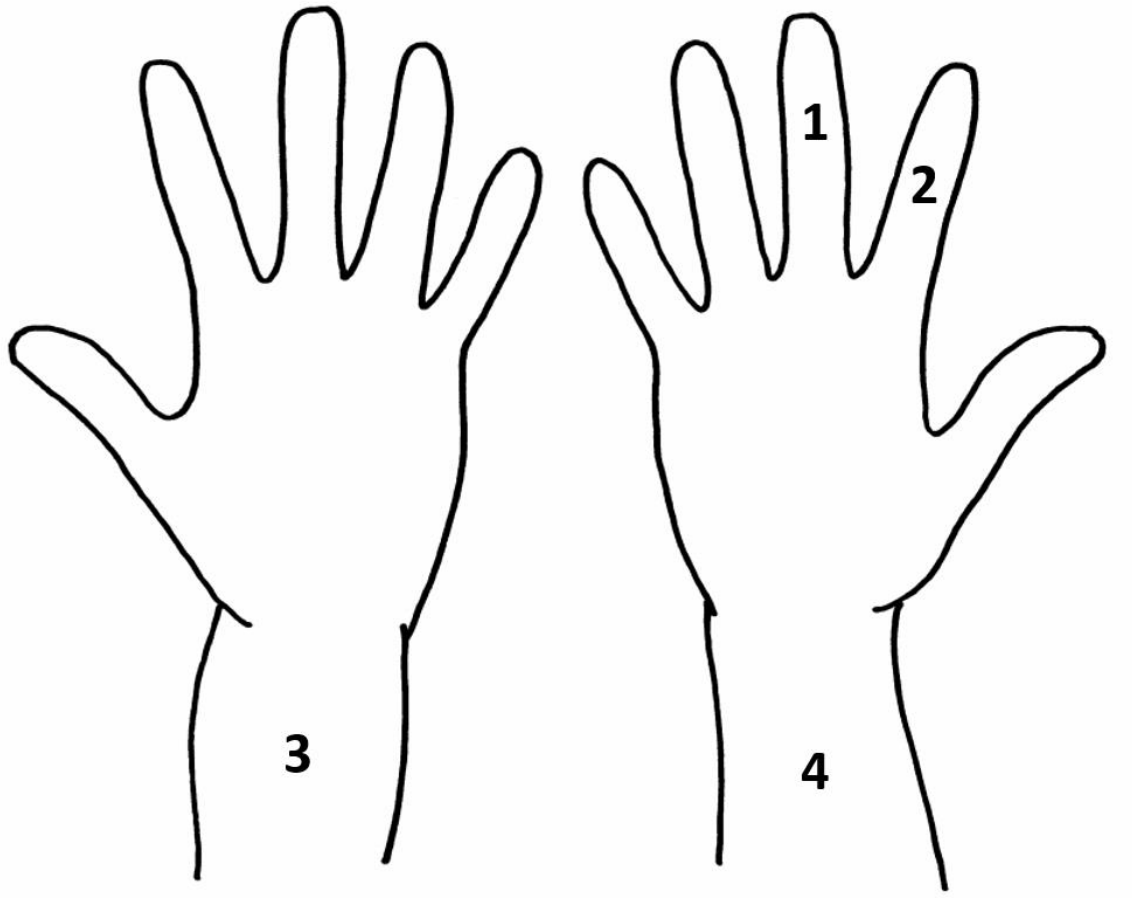


Figure 1: Placement of Electrodes on Left and Right Hands

Face

6 High on right forehead near hairline

7 Center of forehead ~2 cm above brow line

8 Above right eye and eyebrow

9 Right of right eye

10 Below right eye - careful not too close - skin is sensitive here

11 Most prominent point of right cheek bone

12 Above and slightly to right of mouth “dimple” area

13 Left of left eye

IMPORTANT: This diagram is mirrored for use while looking in mirror

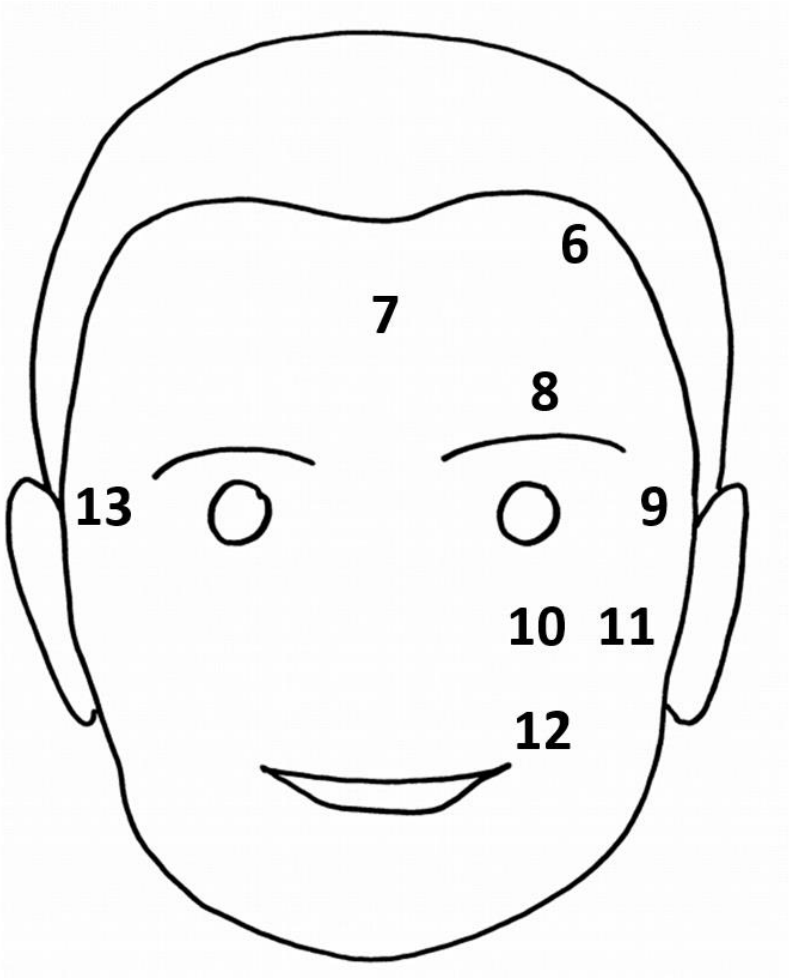


Figure 2: Placement of Electrodes on Face

The electrodes used in this study were MVAP-II Electrodes containing a Silver/Silver Chloride Sensing Element with Hydro Gel and manufactured by MVAP Medical Supplies 1415 Lawrence Drive, Newbury Park, CA 91320. During early testing two other electrode types were evaluated: The Skintact Premier 3415 by Leonhard Lang GmbH and TD-141C square cloth electrodes from Florida Research Instruments. The Skintact electrodes adhered well but were uncomfortable to remove after testing. The Florida Research Instruments electrodes were more comfortable but came off several times during evaluation. These observations are noted for the adhesive only; no comparison of the relative electrical signal performance was made.

3.3. BioRadio mounting and cabling

A seemingly simple but significant issue was mounting the BioRadio uniformly and securely. The BioRadio is equipped with a removable belt clip however since the accelerometer and gyroscope are internal to the radio a uniform mounting independent of clothing was desired. The characteristics of the radio attached to an elastic waist band might vary significantly versus one clipped to a tighter belt.

For the head radio the first attempts were to simply clip the radio onto the straps of the Oculus DK2. The Oculus is fairly immobile on the head however the BioRadio moved significantly when just clipped to the strap. A big improvement in mounting was made by using a plastic mounting bracket modified from an inexpensive LED headlamp which was secured to the straps at the cross point directly in the back of the head. The BioRadio clip was still used but given the thickness of the plastic bracket the radio's

movement independent of the head was significantly reduced as shown in the right hand picture in Figure 3.

Figure 3: “Head” BioRadio mounting improvements

In order to eliminate the possibility of clothing affecting the motion capture of the “body” radio a back supporting belt was utilized. This belt attaches securely around the waist and the Velcro closures were used to hold the body radio tightly against the right side of the waist. Additionally, it was possible to also use the Velcro flaps to secure the cables and sensor pods associated with the RIP belts.

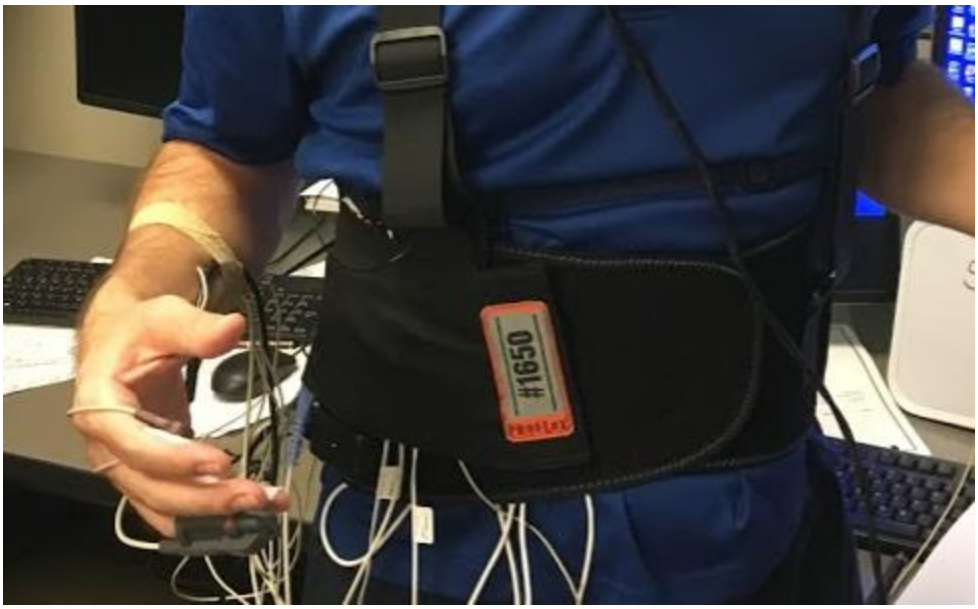


Figure 4: Body BioRadio mounting with Back Support Belt

As can be seen in these photographs, cable management remained somewhat cumbersome. This is a problem for several reasons. First the subject's movement is somewhat limited. This did not prove to be an issue for these activities that consisted only of sitting and standing in a limited area but it will be a greater problem as movement is increased. Directly related to this is the fact that the cable can become snagged and disconnect during the activities. This required special attention especially with respect to the ergonomic armrests and adjustment knobs on the chair. Finally cable movement can induce noise into the signals. Best practices include taping or affixing the cables tightly to the body but this was not practical in a non-medical setting. Future setups would benefit from a fixed harness where the cables are joined into less cumbersome bundles. Once wireless transmission and device power reaches maturity eliminating the cables completely through the use of Bluetooth LE enabled sensors would result in a much more pleasant experience for the subject.

3.3.1 Video Collection and Event Markers

All data collection experiments were recorded with a high definition video recorder and external microphone. This video and audio record proved very valuable when labeling the sessions. In addition, the marker functionality of the BioRadio was used to mark key segments such as the start of a VR application in the data set.

3.3.2 Subject Feedback Regarding Arousal and Valence

Initial experimentation showed that getting consistent and reliable feedback from the subject is challenging. It is quite difficult to describe many of the experiences in consistent emotional terms. Indeed, the question "How did that make you feel?" is an opened ended on often used in therapy. Even members of the research team who were familiar with the classification of emotion and the arousal-valence model struggled to enunciate what types of emotion a specific video or game induced.

Initial attempts to simplify this process included several variation of multiple choice selections. One was specifically based on the six universal emotion categories used by Ekman and Friesen [3] which are: happiness, anger, sadness, disgust, surprise, and fear. Unfortunately, while these emotions may be present in all subjects they did not cover the range of emotion reported during the experimentation. After watching what could be best described as either a relaxing or boring video there is no best fit response available with these six categories.

Check the box to the right that best represents how you felt during the session.

		A little						A lot
Session 1	Emotion	1	2	3	4	5	6	7
Introduction to Virtual Reality	Excited							
	Happy							
	Sad							
	Angry							
	Scared							
	Tender							

Figure 5: Emotion and Range Subject Response Form – too complex

Figure 5 shows a second iteration, which included a listing of emotions along with a ranking. Subjects were asked to complete the table after each session. Two fundamental issues arouse with the use of this form. First the revised categories still did not match with the subject's expressed emotion during the simulation. Second the addition of a range considerably lengthened the time that subjects required to complete the feedback.

Another issue arose once the testing was moved exclusively to the Virtual Reality environment. The initial thinking was that the subjects would welcome a brief break between the 3 to 8 minute sessions to remove the Virtual Reality headset and complete the survey form. However, the frequent removal of the headset proved to be annoying and broke the flow of the simulations. Once "inside" the Virtual Reality world it was much preferred to continue with the sessions. Furthermore, many of the electrodes and wires are located on the face and hands so the removal of the headset was much more

cumbersome than it would be during traditional usage. This also increased the risk that one of the cables or electrodes could be disconnected.

The final methodology employed was a simplified version of the arousal-valence model. Instead of removing the headset to fill out a form, the subject was asked verbally the following questions after each session:

Did you find this [movie, game, demo] exciting, relaxing, or neutral?

Did you find this [movie, game, demo] pleasant, unpleasant, or neutral?

While there was still some hesitation on the subject's part especially during longer sessions that had multiple parts this simplified oral response method worked much better than the prior methods.

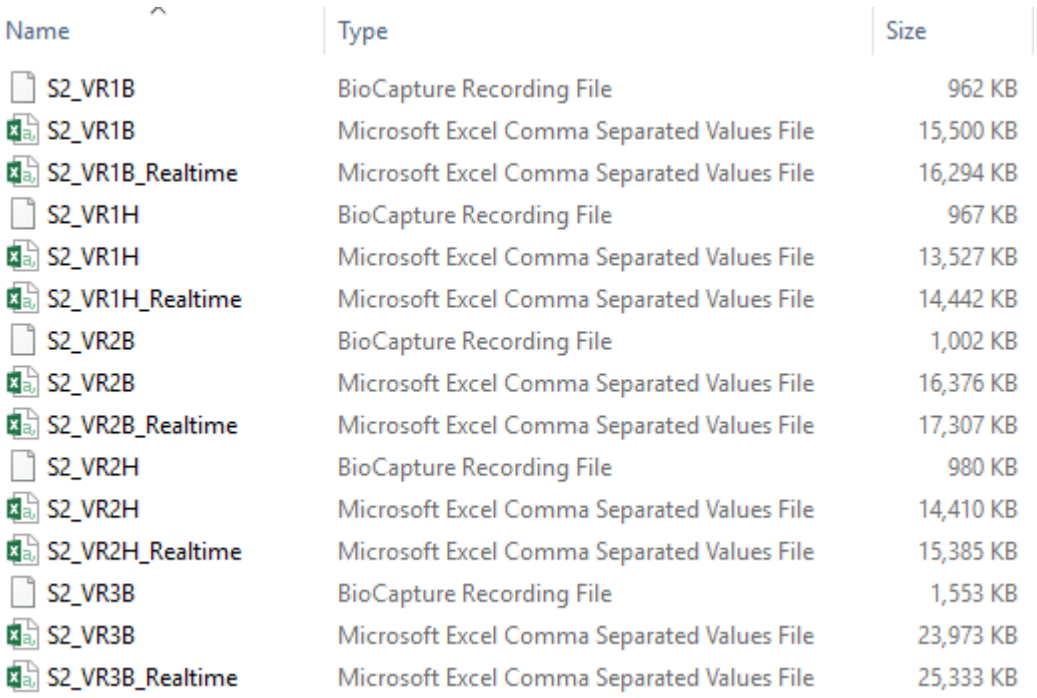
3.4 Signal Processing and Classification

3.4.1 Data Export

The collected data was stored on a laptop running Windows 10 and two instances of the BioCapture program. Each instance of BioCapture linked to one radio: Instance on left was linked to the head radio, instance on right was linked to the body radio. For consistency the recording was started on the head radio first and then on the body radio. The typical offset involved with switching instances and setting up the second recording was approximately 17 seconds. The keyboard was configured for a marker in the head radio instance of BioCapture. All marker data was captured in the head instance. The naming convention used was Sx_VRy[H,B].bcrx for subject x and session y and Head, Body.

After the session was completed the files were exported from the BioCapture program into standard comma delimited text (.csv) format. Two versions were exported, one with RealTime information (used for synchronization) and an ElapsedTime version (smaller and easier to handle in MATLAB).

Given the 250 Hz sampling rate each minute of collected data generated 15,000 rows in the table. The total number of rows depends on the session length and ranges from approximately 70,000 to 140,000 rows for sessions 1 - 6. Due to the fact that it was left to the subject as to how long to continue Session 7 has a broader range and can exceed 250,000 rows if the subject completes the entire game. The head configuration has 13 columns and the body configuration has 16 columns.

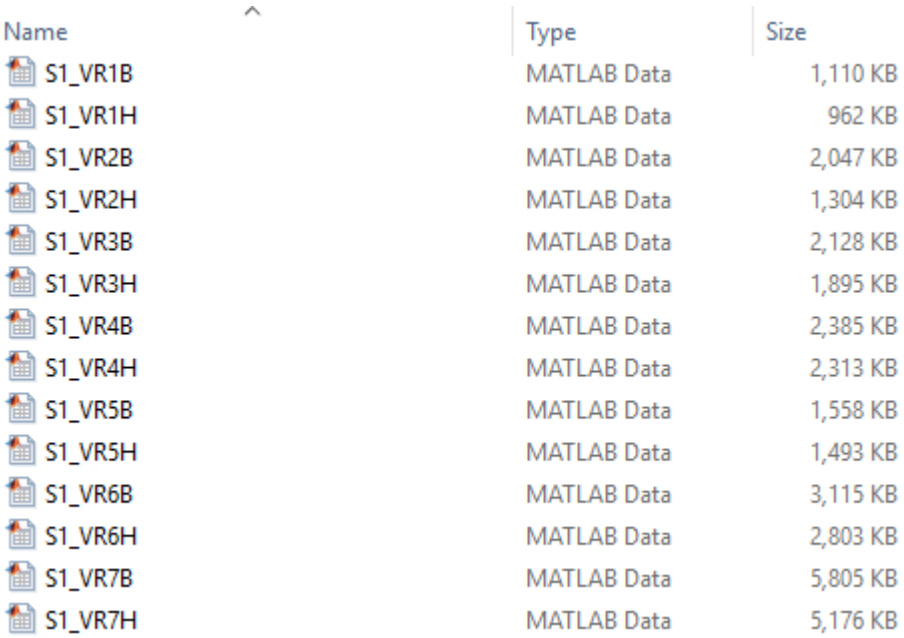


Name	Type	Size
S2_VR1B	BioCapture Recording File	962 KB
S2_VR1B	Microsoft Excel Comma Separated Values File	15,500 KB
S2_VR1B_Realtime	Microsoft Excel Comma Separated Values File	16,294 KB
S2_VR1H	BioCapture Recording File	967 KB
S2_VR1H	Microsoft Excel Comma Separated Values File	13,527 KB
S2_VR1H_Realtime	Microsoft Excel Comma Separated Values File	14,442 KB
S2_VR2B	BioCapture Recording File	1,002 KB
S2_VR2B	Microsoft Excel Comma Separated Values File	16,376 KB
S2_VR2B_Realtime	Microsoft Excel Comma Separated Values File	17,307 KB
S2_VR2H	BioCapture Recording File	980 KB
S2_VR2H	Microsoft Excel Comma Separated Values File	14,410 KB
S2_VR2H_Realtime	Microsoft Excel Comma Separated Values File	15,385 KB
S2_VR3B	BioCapture Recording File	1,553 KB
S2_VR3B	Microsoft Excel Comma Separated Values File	23,973 KB
S2_VR3B_Realtime	Microsoft Excel Comma Separated Values File	25,333 KB

Figure 6: Directory Listing showing Data Files and Size after Export

3.4.2 Data Import, Table Join, and Labeling

After conversion to .csv format each of the 14 data files (7 sessions x 2 for Head and Body) was imported in to a MATLAB table and stored on the University server. MATLAB Version R2016a was used for this analysis. Product details can be found on the MathWorks website [52]



Name	Type	Size
S1_VR1B	MATLAB Data	1,110 KB
S1_VR1H	MATLAB Data	962 KB
S1_VR2B	MATLAB Data	2,047 KB
S1_VR2H	MATLAB Data	1,304 KB
S1_VR3B	MATLAB Data	2,128 KB
S1_VR3H	MATLAB Data	1,895 KB
S1_VR4B	MATLAB Data	2,385 KB
S1_VR4H	MATLAB Data	2,313 KB
S1_VR5B	MATLAB Data	1,558 KB
S1_VR5H	MATLAB Data	1,493 KB
S1_VR6B	MATLAB Data	3,115 KB
S1_VR6H	MATLAB Data	2,803 KB
S1_VR7B	MATLAB Data	5,805 KB
S1_VR7H	MATLAB Data	5,176 KB

Figure 7: Raw Subject 1 Data after Import as MATLAB Table

Since the head and body recording are separate they need to be joined prior to classification. Unfortunately, there is no common signal nor ability to add a marker in each file. There are known techniques of synchronizing the files based on cross correlation however given that each of the signals is discrete and the times involved are based on human reaction the files were synchronized using the real time data available via the BioRadio. Specifically, an offset was calculated by subtracting the delay from

the start of the head recording to the start of the body recording and this was used to align the rows prior to performing a table join. In addition, the start and stop times were also used to discard the setup and takedown segments of each session.

A separate table containing column vectors with the subject and session data was also created. This metadata was present in the file name and would be lost when all of the data was combined. The table and its column vectors were joined to the initial table. Classification labeling within each segment was much more manual and required the time information gleaned from the video. A point was made to include a start mark (by pressing the 'S' button on the laptop) in the head file that was audibly and visually visible in the video. Since this data was also clearly present in the data file it served as the alignment index between the video data and the signal data. For several of the sessions the activities were further broken down into segments as previously described in the subject self-reporting section. The video was viewed and time manually input into a spreadsheet to convert to elapsed time in the data file.

	A	B	C	D	E	F	G	H	I
1	**S1_VR3**	MVI_004	Real Time		Elapsed Time	Classification			
2			S1_VR3H	S1_VR3B		Segment	Arousal	Valence	
3	Start Head Recording	0:17:08	15:29:41.606		0				
4	Start Body Recording	0:17:24	15:29:58	15:29:58.624	17.02				
5	Start of Rollercoaster [Mark]	0:17:41	15:30:14.966		33.360	void	99	99	<- key
6	Start of Ascent up Ramp	0:17:53	15:30:27		45.36	RC_ramp	1	-1	
7	Start of Drop	0:18:19	15:30:53		71.36	RC_ride	1	-1	
8	Stop Rollercoaster	0:19:31	15:32:05		143.36	void	99	99	
9	Stop of Session [Mark]	0:19:44	15:32:18.882		157.276	void	99	99	
10	Start Standing	0:20:03	15:32:37		175.36	void	99	99	
11	Finish Standing	0:20:14	15:32:48		186.36	void	99	99	
12	Jump into Unknown [Mark]	0:20:30	15:33:04.066		202.460	void	99	99	
13	Start of View from cliff	0:20:43	15:33:17		215.36	Cliff_high	1	1	
14	Pushed in VR	0:21:40	15:34:14		272.36	Cliff_swinging	1	1	
15	Jump into Unknown Finish	0:22:10	15:34:44		302.36				
16	Ending [Mark]	0:22:16	15:34:50.054		308.448				
17									
18			HtoB Offset	00:00:17.018	use 17.016 even of 4ms sample to keep table lengths equal				

Figure 8: Screenshot of Excel Spreadsheet used for Timing Synchronization

MATLAB was used to process the raw data into a single “mega table” that included the 24 signal data, subject, session, self-reported arousal, self-reported valence, and segment column vectors. In keeping with good programming practice the experiment specific information was imported from separate .csv files with the hope that future sessions could be processed without modifications to the MATLAB code itself.

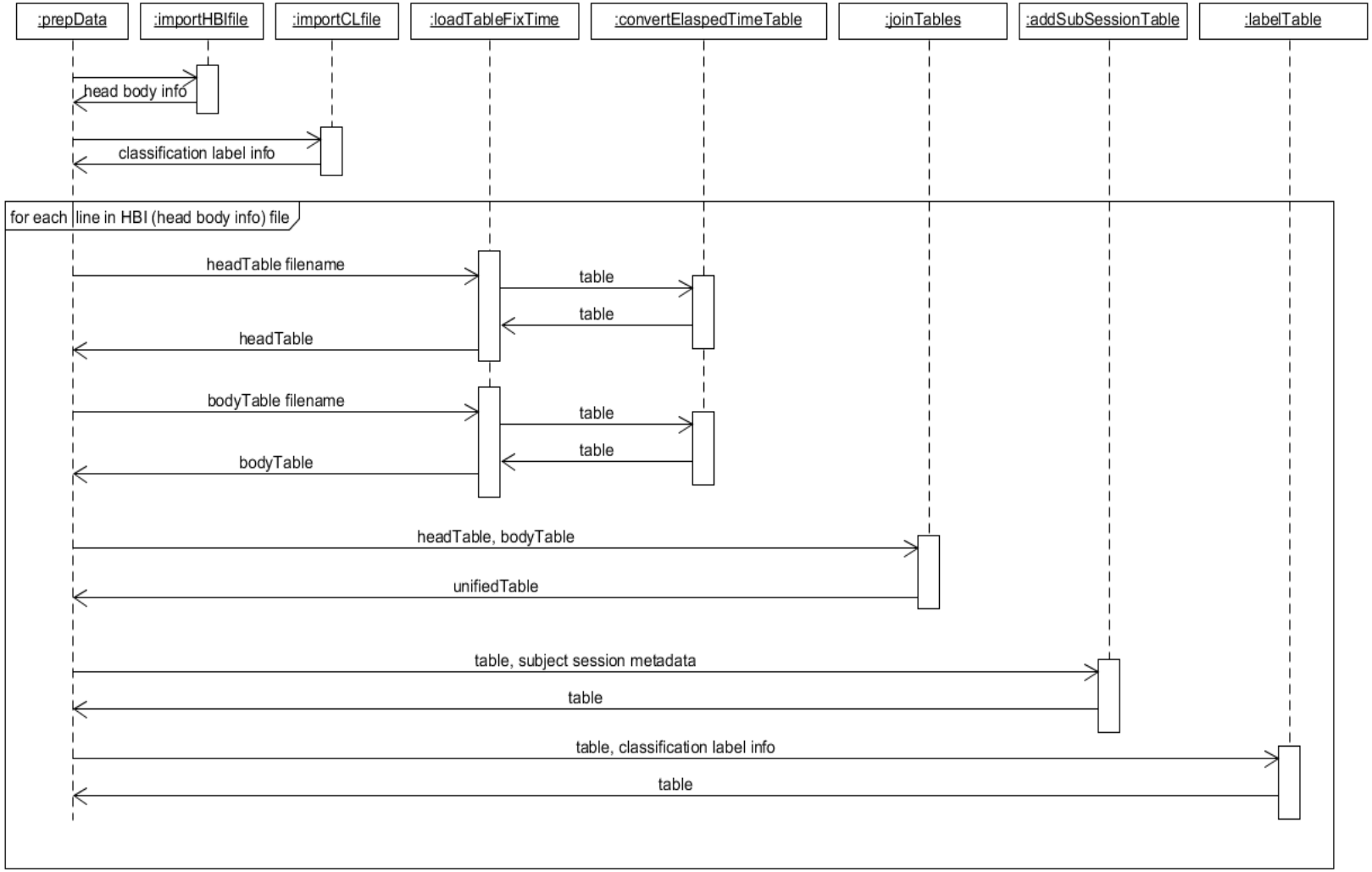


Figure 9: Sequence Diagram of Import from .csv

3.4.3 Feature Extraction

Feature extraction was performed in a series of several experiments once the dataset was available. For the very first runs a simple mean and standard deviation feature table was built. Given the 24 time based signal present in the dataset this yielded a table containing 48 feature vectors. A time sweep was performed from 1 second to 20 seconds to see what epoch size yielded the best results.

A second more complex set of feature extraction was performed using existing code from the research group that extracted a total of 90 features for each signal.

3.5 Institutional Review Board

As this research involved human subjects, review and approval by the Texas State Intuitional Review Board was required.

“Texas State University, by action of the President, has established an institutional review board (IRB) to review human subject research. This board is supported by The Office of Research Integrity and Compliance (ORIC). The IRB reviews research that is conducted or supported by the Texas State University faculty, students or staff in order to determine that the rights and welfare of the human subjects are adequately protected. The IRB is guided by the ethical principles described in the 'Belmont Report' and by the regulations of the U.S. Department of Health and Human Services found at Title 45 Code of Federal Regulations, Part 46. Texas State maintains an approved Federal wide Assurance (FWA00000191) of Compliance with the Office for Human Research Protection (OHRP).” [53]

Application #2016M7258 Version #1 was approved 7/12/2016 and expires 6/30/2017. All subjects signed an informed consent form prior to the virtual reality sessions. Subjects were briefed on the content and approximate duration of each session immediately prior to the session during the data collection. Subjects were periodically reminded that they were free to stop at any time without repercussion or harm to the research. Subjects were also told to be aware of the possibility of nausea and read/accepted the in session Oculus health warning.

The collected dataset does not contain subject names or other known identifiable information. All data is stored on the Texas State TRACS system with controlled access by Dr. Vangelis Metsis.

4 EXPERIMENTS AND RESULTS

4.1 Self-Reported Data – Range of Responses during Simulations

Table 5: Summary of Subject Reponses

Total Responses - 5 Subjects

Data File	Description	Arousal E	Arousal R	Arousal N	Valence P	Valence U	Valence N
Sx_VR1	Introduction to Virtual Reality Demo	3	1	1	5	0	0
Sx_VR2	The Rose and I Movie	0	3	2	3	0	2
Sx_VR3	Rollercoaster 3D Movie	5	0	0	3	1	1
Sx_VR3	Pendulum Swing 3D Movie	5	0	0	4	0	1
Sx_VR4	In Cell Game	3	0	2	3	0	2
Sx_VR5	Lost Movie	2	0	3	1	1	3
Sx_VR6	Dream Deck Demo: Overall	3	0	2	1	0	4
Sx_VR6	Dream Deck Demo: City Scene (Height)	2	1	2	3	0	2
Sx_VR6	Dream Deck Demo: Alien (Creepy)	1	0	4	1	1	3
Sx_VR6	Dream Deck Demo: Dinosaur (Scary)	4	0	1	1	2	2
Sx_VR7	Lucky's Tale Game	2	0	3	3	1	1
Sum		30	5	20	28	6	21

E = Exciting
R = Relaxing
N = Neutral

P = Pleasant
U = Unpleasant
N = Neutral

The subject self-reported data to the questions described in Section 3.3.3 are shown in Table 5. The results are very asymmetrical with the majority of the segments rated as ‘Exciting’ and ‘Pleasant’. This is likely due to the conservative selection of stimuli and the limited number of subjects. For example, only one subject expressed any trepidation regarding heights and therefore the Pendulum Swing and City Scene which both involved a view from very high perspective with a large potential drop off was not rated as unpleasant. By subject data is shown in Table 6 and Table 7.

Table 6: Subject 1-3 Detailed Responses

Oculus VR Subject Responses

Data File	Description	S1 Arousal: Exciting	S1 Arousal: Relaxing	S1 Arousal: Neutral	S1 Valence: Pleasant	S1 Valence: Unpleasant	S1 Valence: Neutral	S2 Arousal: Exciting	S2 Arousal: Relaxing	S2 Arousal: Neutral	S2 Valence: Pleasant	S2 Valence: Unpleasant	S2 Valence: Neutral	S3 Arousal: Exciting	S3 Arousal: Relaxing	S3 Arousal: Neutral	S3 Valence: Pleasant	S3 Valence: Unpleasant	S3 Valence: Neutral
Sx_VR1	Introduction to Virtual Reality Demo	1			1			1			1				1		1		
Sx_VR2	The Rose and I Movie			1			1		1		1					1	1		
Sx_VR3	Rollercoaster 3D Movie	1				1		1			1			1			1		
Sx_VR3	Pendulum Swing 3D Movie	1			1			1			1			1					1
Sx_VR4	In Cell Game			1	1					1			1	1			1		
Sx_VR5	Lost Movie	1				1				1			1			1	1		
Sx_VR6	Dream Deck Demo: Overall	1					1	1					1			1	1		
Sx_VR6	Dream Deck Demo: City Scene (Height)	1					1			1			1			1	1		
Sx_VR6	Dream Deck Demo: Alien (Creepy)			1		1				1			1			1			1
Sx_VR6	Dream Deck Demo: Dinosaur (Scary)	1				1		1					1	1			1		
Sx_VR7	Lucky's Tale Game			1			1			1		1				1	1		

Table 7: Subject 4-5 Detailed Responses

Oculus VR Subject Responses

Data File	Description	S4 Arousal: Exciting	S4 Arousal: Relaxing	S4 Arousal: Neutral	S4 Valence: Pleasant	S4 Valence: Unpleasant	S4 Valence: Neutral	S5 Arousal: Exciting	S5 Arousal: Relaxing	S5 Arousal: Neutral	S5 Valence: Pleasant	S5 Valence: Unpleasant	S5 Valence: Neutral
Sx_VR1	Introduction to Virtual Reality Demo			1	1			1			1		
Sx_VR2	The Rose and I Movie		1		1				1				1
Sx_VR3	Rollercoaster 3D Movie	1					1	1			1		
Sx_VR3	Pendulum Swing 3D Movie	1			1			1			1		
Sx_VR4	In Cell Game	1					1	1			1		
Sx_VR5	Lost Movie	1					1			1			1
Sx_VR6	Dream Deck Demo: Overall	1					1			1			1
Sx_VR6	Dream Deck Demo: City Scene (Height)	1			1				1		1		
Sx_VR6	Dream Deck Demo: Alien (Creepy)			1			1	1			1		
Sx_VR6	Dream Deck Demo: Dinosaur (Scary)	1				1				1			1
Sx_VR7	Lucky's Tale Game	1			1			1			1		

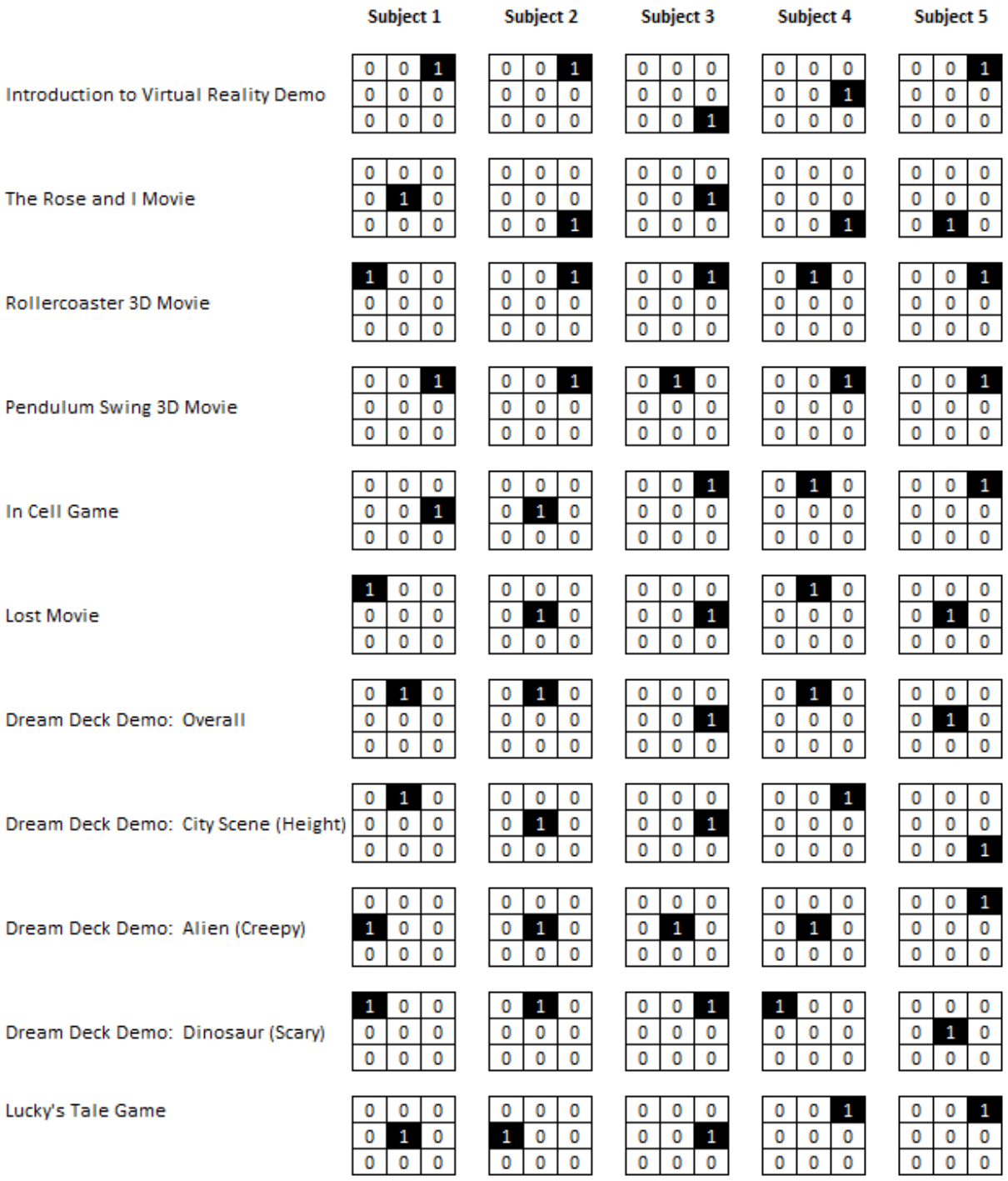


Figure 10: Subject Responses marked on Arousal-Valence axis

Figure 10 shows the individual subject responses represented on a 3 x 3 grid which reflect the arousal (y-axis) and valence (x-axis) of the rated response.

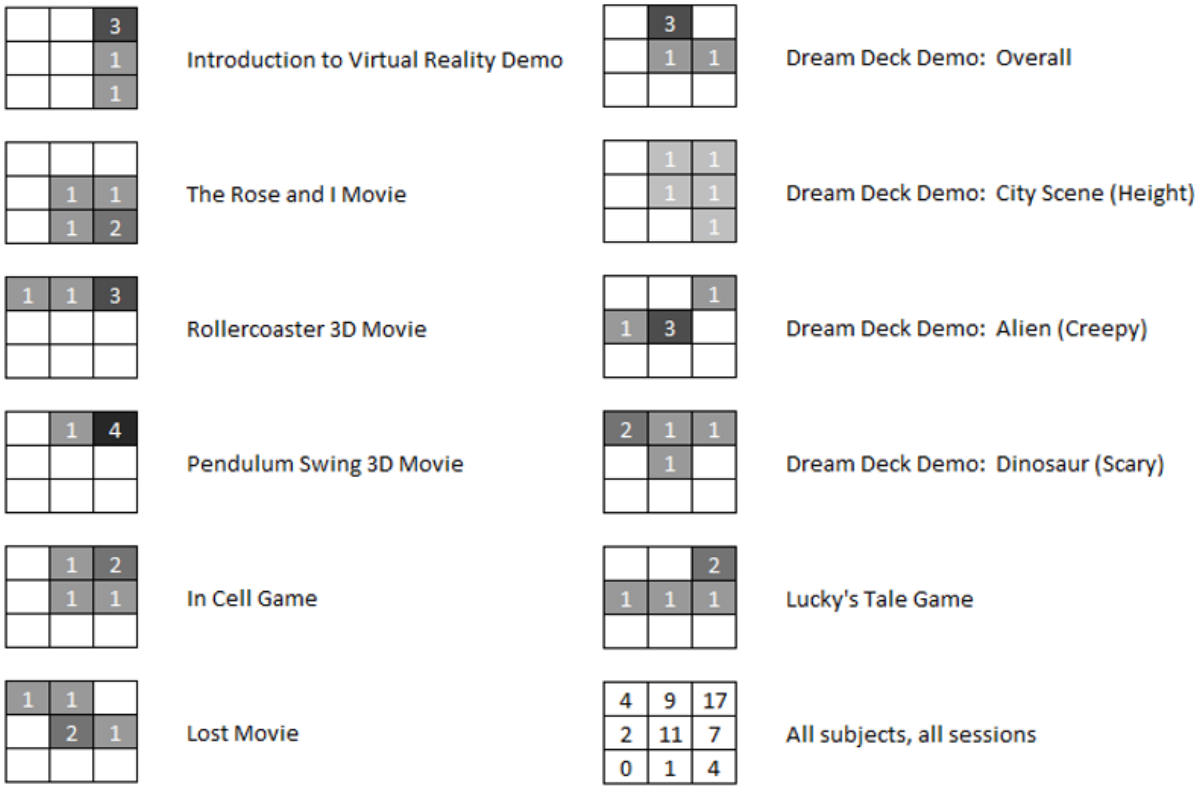


Figure 11: Summary of all Subject Responses marked on Arousal-Valence axis

Figure 11 shows the sum of the total subject responses represented on a 3 x 3 grid which reflect the arousal (y-axis) and valence (x-axis) of the rated response.

4.2 Initial Signal Analysis and Data Conversion

Signals were plotted using the BioCapture software tool provided by the BioRadio vendor for quick inspection and verification that the signal data was good.

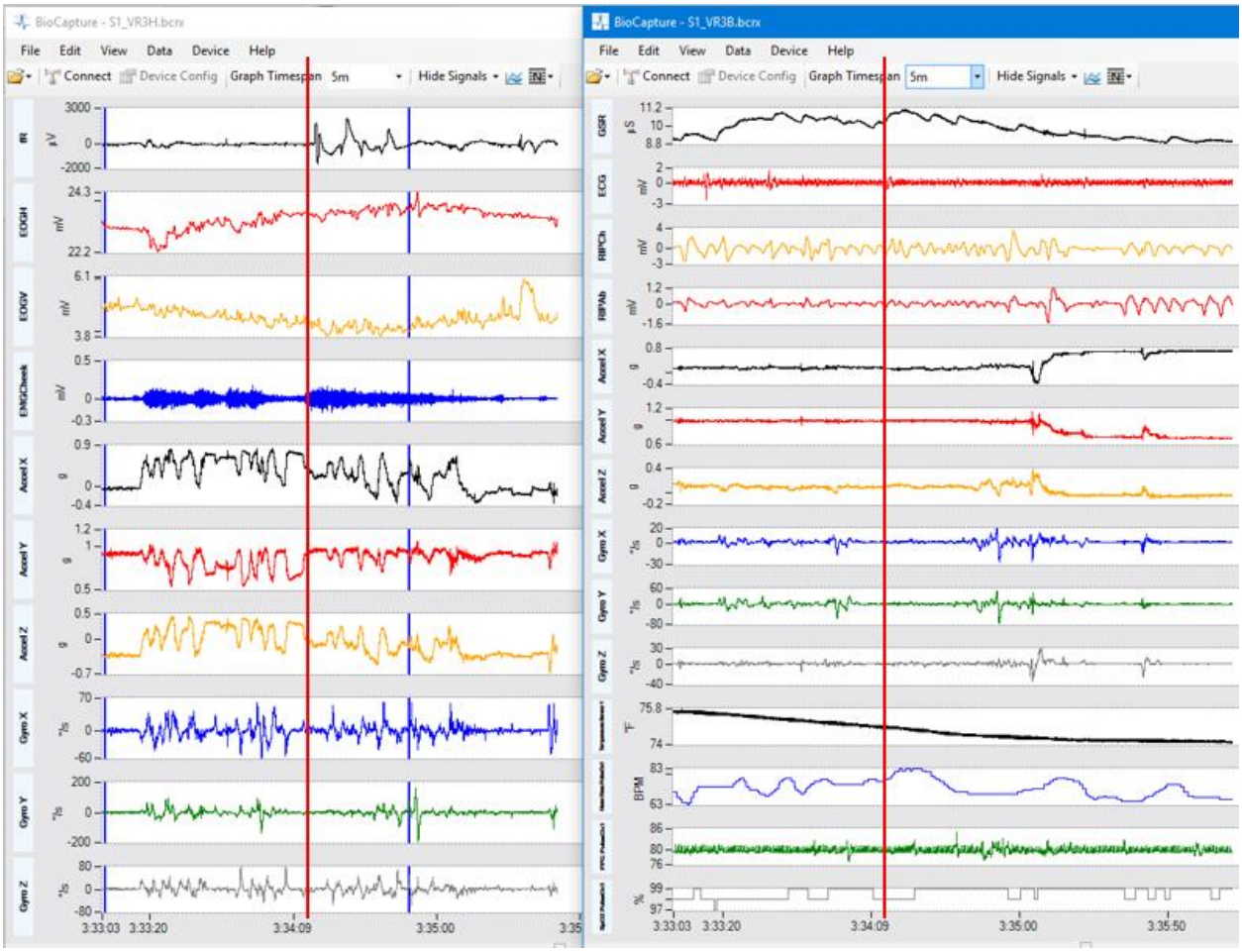


Figure 12: Side by side screenshot of Signal Data shown in BioCapture Software

Figure 12 shows an initial visualization of the signals during an early run. The signals on the left are from the "head" BioRadio and the signals on the right are from the "body" BioRadio. The red line on these graphs represent the moment when the subject is pushed from a cliff in the virtual reality simulation. Several interesting and encouraging aspects are present. First the EEG f4 (labeled fR on the figure) shows a distinct change

after the “push”. This is in the absence of a significant change in EOGV and EOGH which could also affect the EEG measurement. The EMG cheek signal shows an increase which would be associated with a smile, laugh, or potentially jaw clench. The GSR is increasing for a period of several seconds which is consistent with a stress or excitement reaction. Finally, the heart rate rises also consistent with an increase in arousal.

4.2.1 Rose and I Movie

The Rose and I Movie was rated as pleasant and relaxing or neutral by all subjects. As such we would not anticipate any significant reactions or events during the course of the session. The graphs below show six selected signals and represent a baseline for comparison. The session itself is approximately 4 minutes long, the graphs show a 90 second window which is similar in duration to the rollercoaster and pendulum swing sessions. At the 45 second mark there is a scene in the movie where a flower sneezes and the main character is startled.

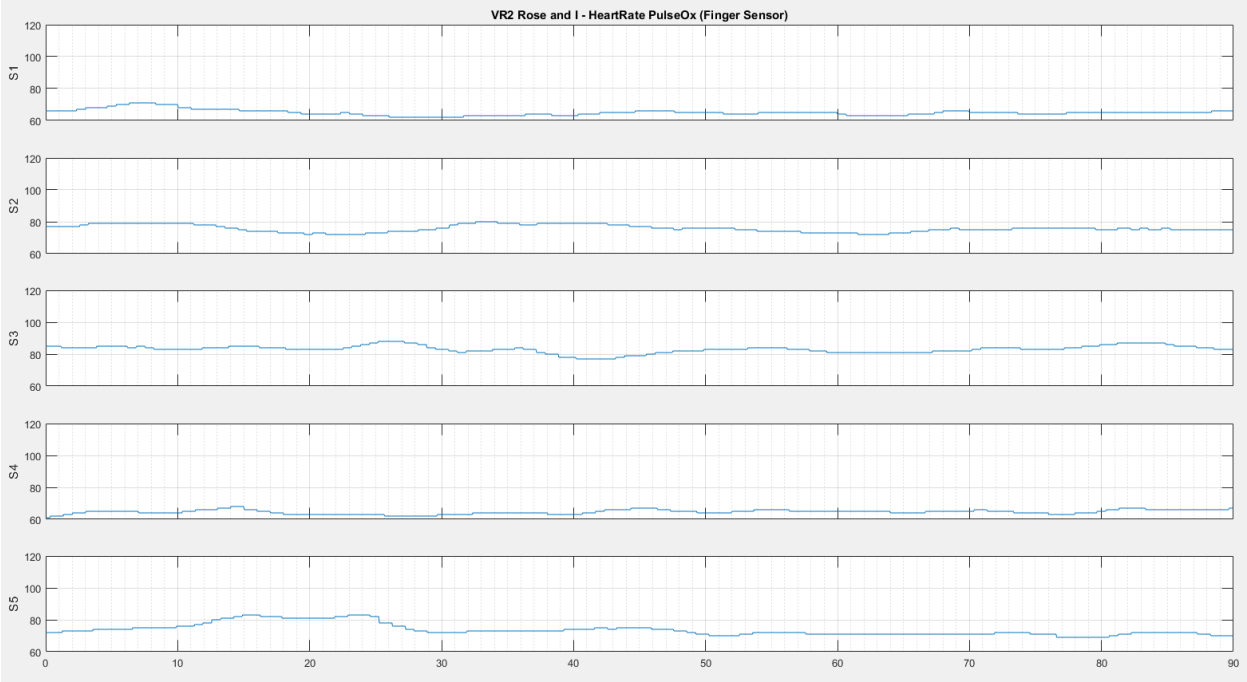


Figure 13: Subject Heart Rate during Rose and I Segment

The heart rate remains relatively low and unchanged throughout this video as expected. There is a difference in the base heart rate among the subjects that is evident during this typically relaxing session.

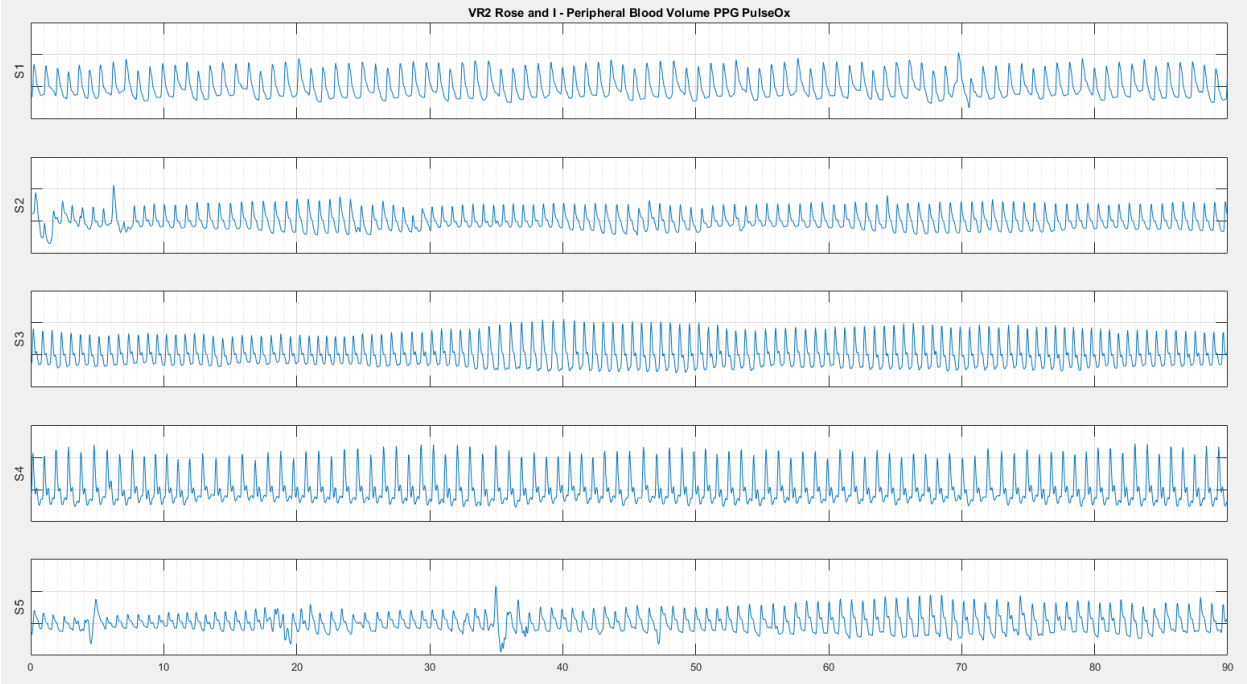


Figure 14: Peripheral Blood Volume during Rose and I Segment

The peripheral blood pulse volume exhibits some variation but with no discernable pattern related to the session stimuli.

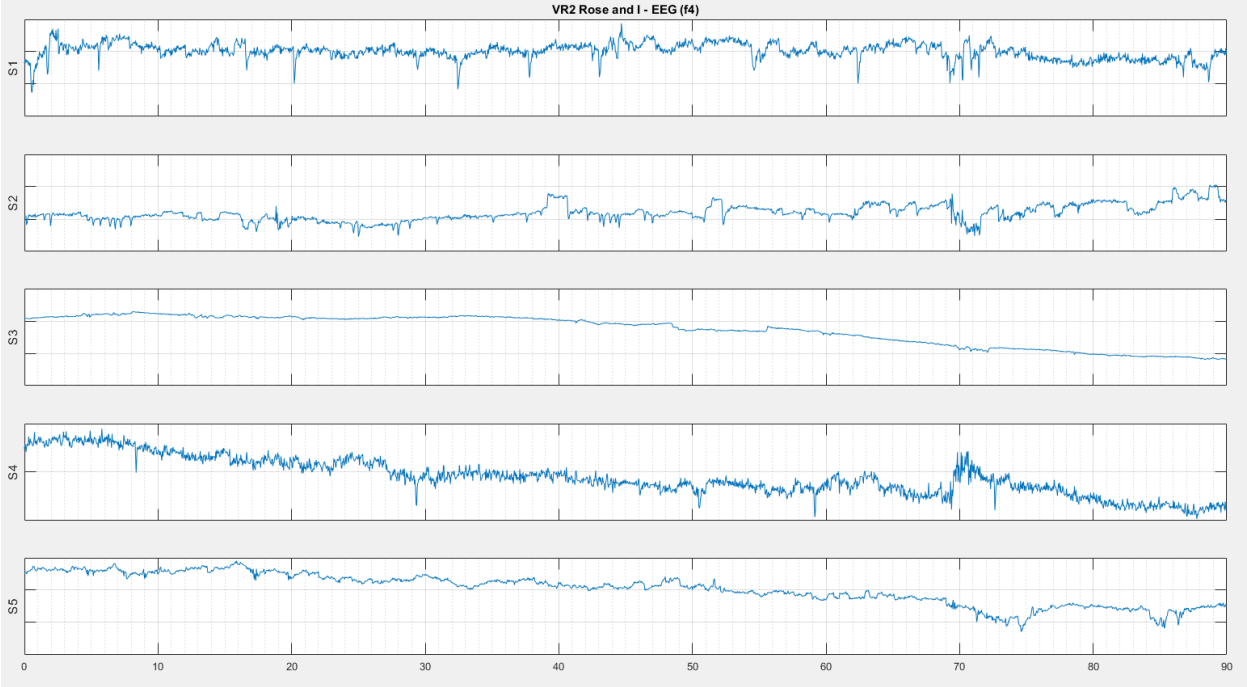


Figure 15: EEG during Rose and I Segment

The EEG f4 signal exhibits some variation but with no discernable pattern related to the session stimuli.

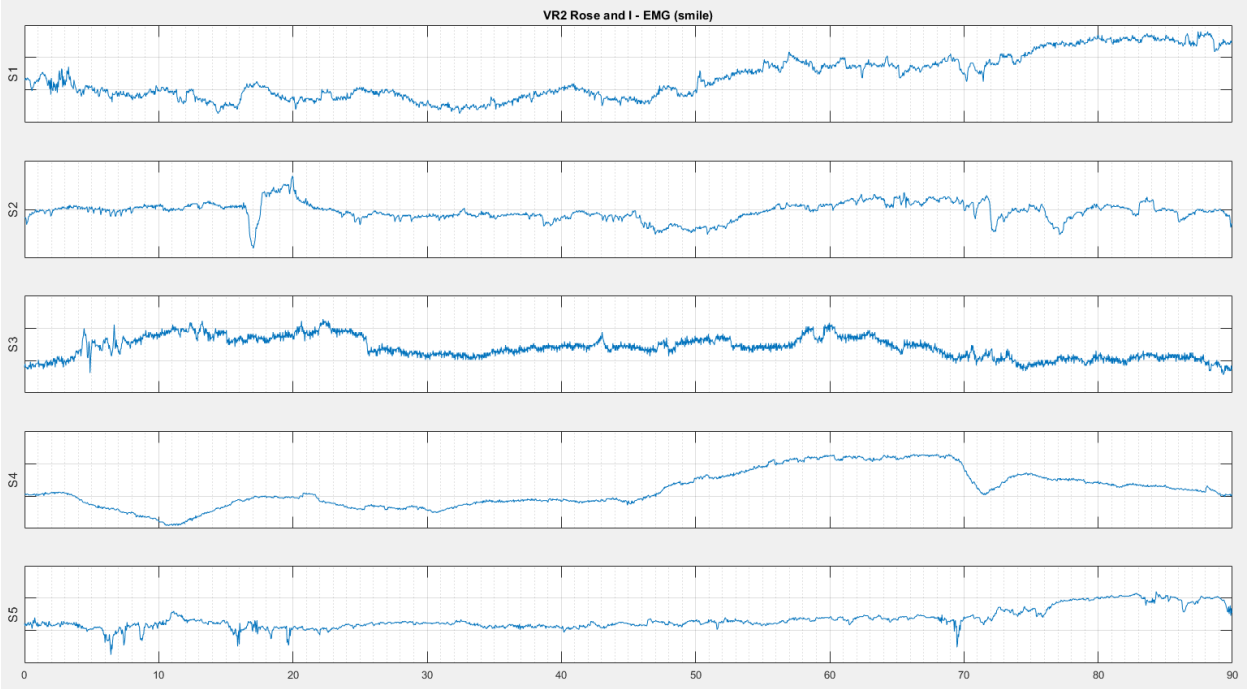


Figure 16: EMG during Rose and I Segment

The EMG signal exhibits some variation but with no discernable pattern related to the session stimuli.

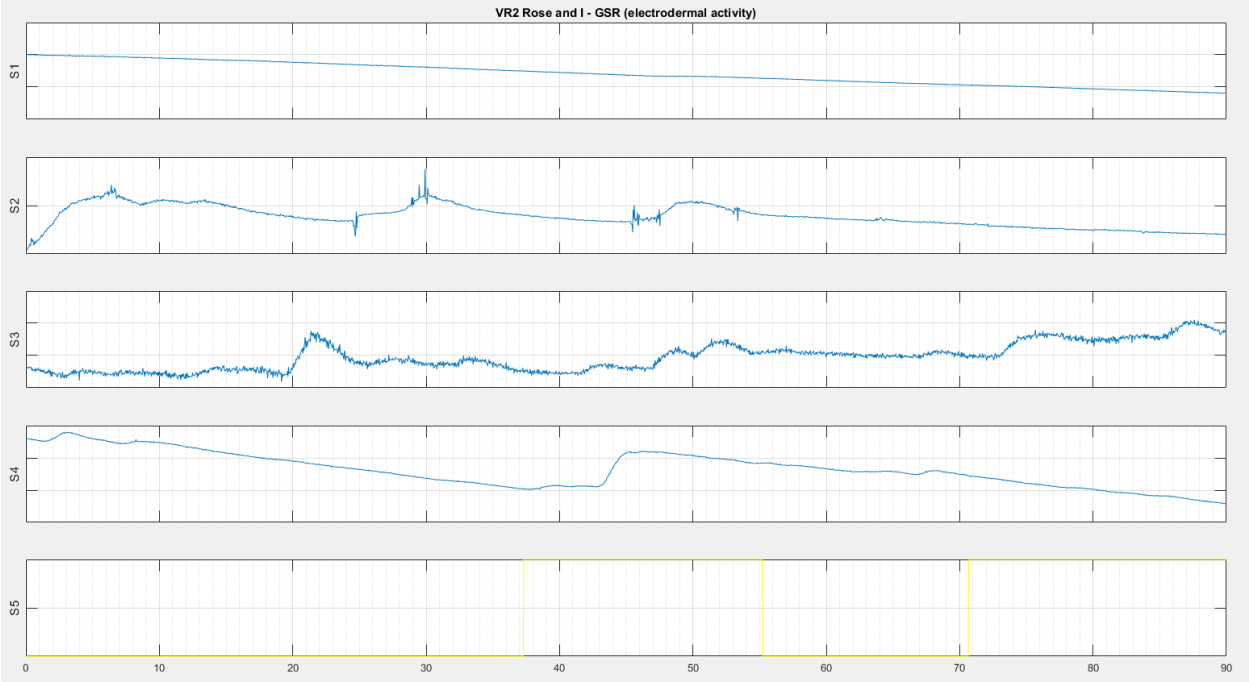


Figure 17: GSR during Rose and I Segment

Subject 3 shows a potential response at time 20 seconds however there is no in session stimuli at this point. Subject 4 shows a response at time 45 seconds which is at the time of the previously mentioned sneeze/startle scene. Subject 2 and 3 have potential responses as well but less pronounced. No response can be seen in Subject 1 data. Unfortunately, Subject 5's data in invalid due to a disconnection of the finger electrode.

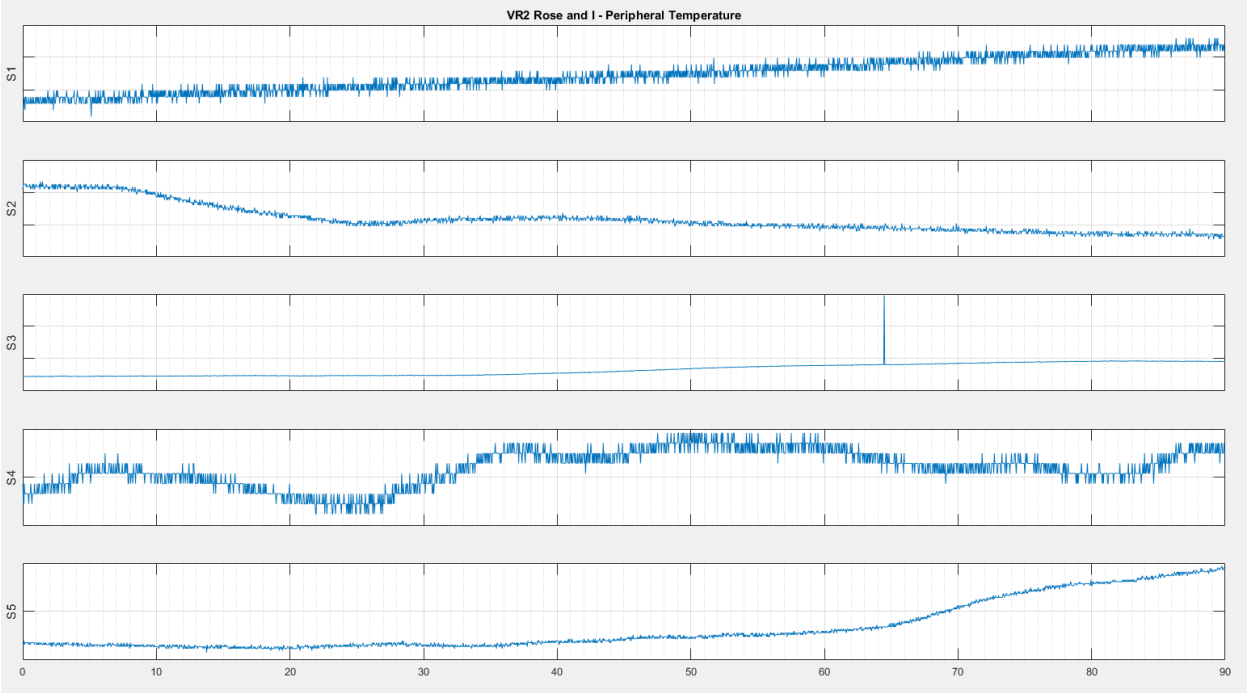


Figure 18: Peripheral Temperature during Rose and I Segment

The peripheral skin temperature for Subjects 1,3,4, and 5 increases during this session while Subject 2 decreases. This is in contrast to the tendency of the peripheral temperature to decrease during the rollercoaster and pendulum swing segments.

4.2.2 Roller Coaster

The rollercoaster segment includes climbing the ramp from time 0 to 24 seconds with the remainder of the time being the actual ride. Subject 2 reported mild nausea immediately following the ramp segment.

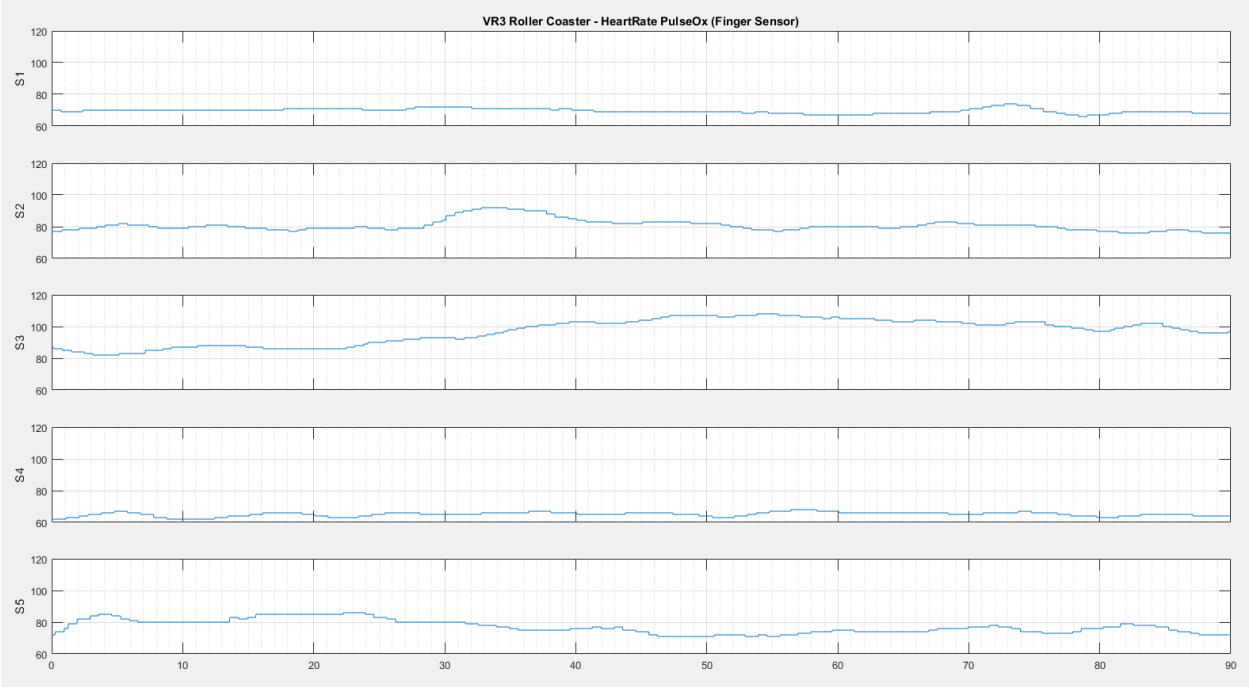


Figure 19: Subject Heart Rate during Roller Coaster Segment

Only Subject 2 who reported mild nausea and Subject 3 showed a significant increase in heart rate during the roller coaster segment. Subjects 1 and 2 had steady heart rates and Subject 5 had slightly decreasing heart rate during the ride segment.

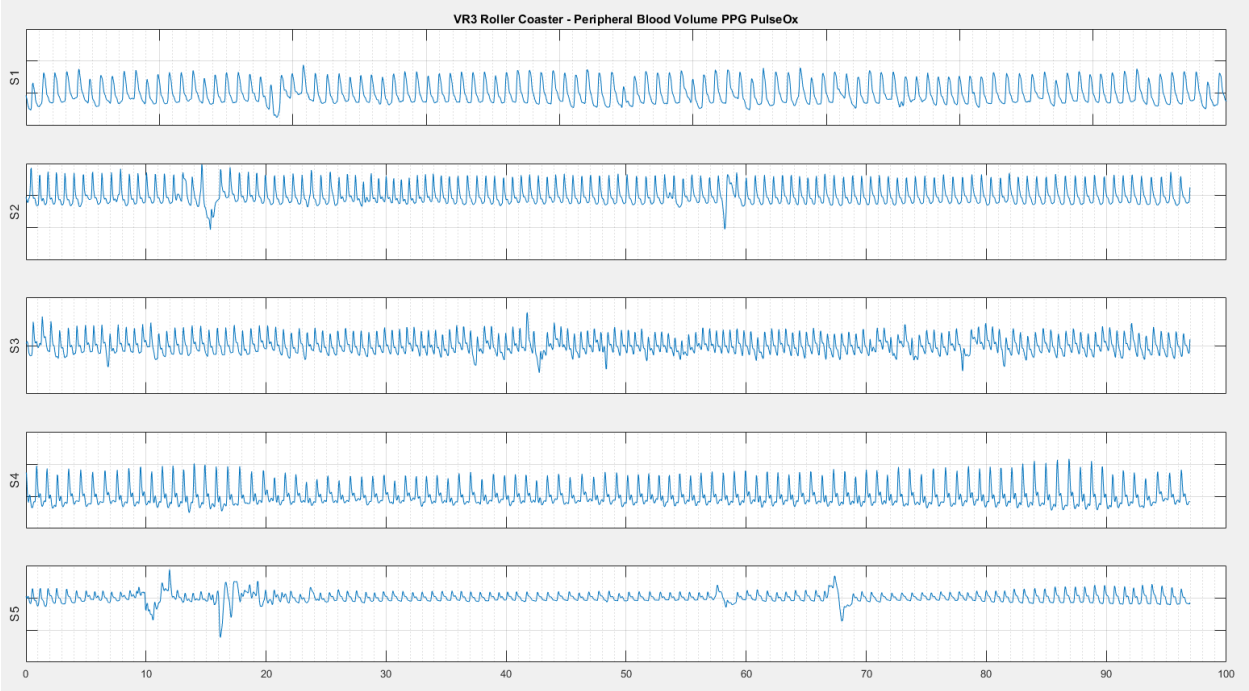


Figure 20: Subject Peripheral Blood Pulse Volume Roller Coaster Segment

The peripheral blood pulse volume exhibits some variation but with no discernable pattern related to the session stimuli.

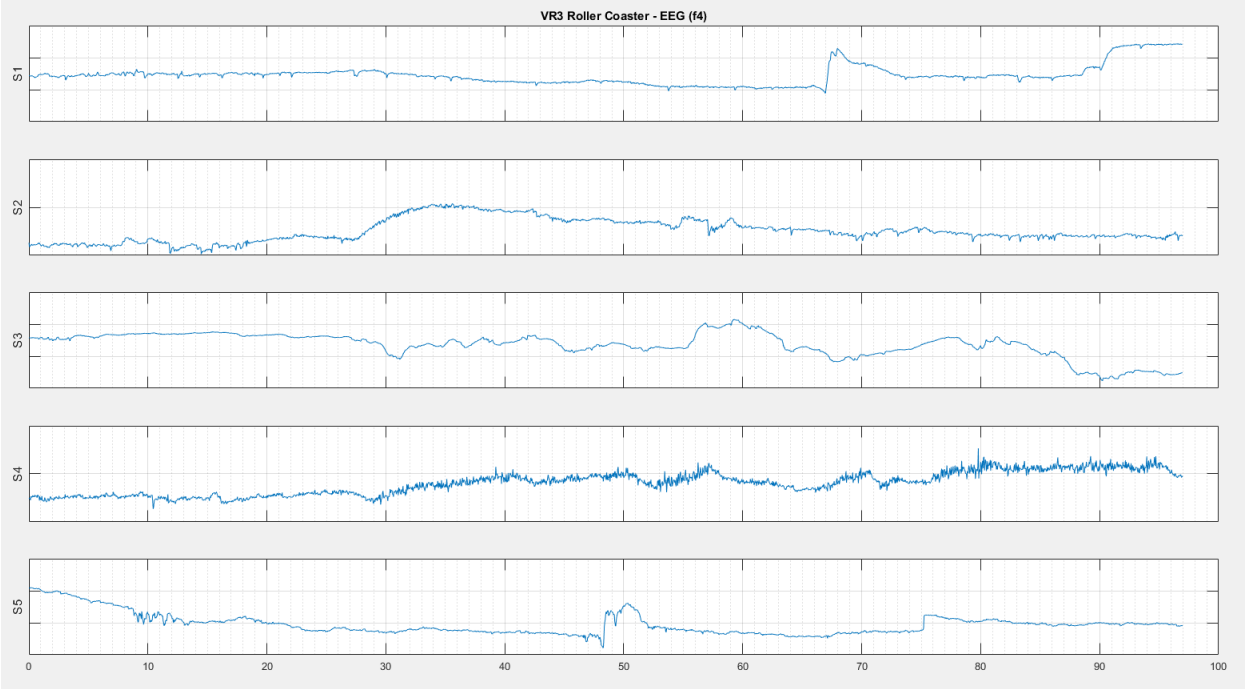


Figure 21: Subject EEG f4 during Roller Coaster Segment

No consistent time related pattern is seen in the EEG f4 signal during the roller coaster segment. Much of the variation here is likely due to the head and eye movement resulting in artifacts in the f4 signal.

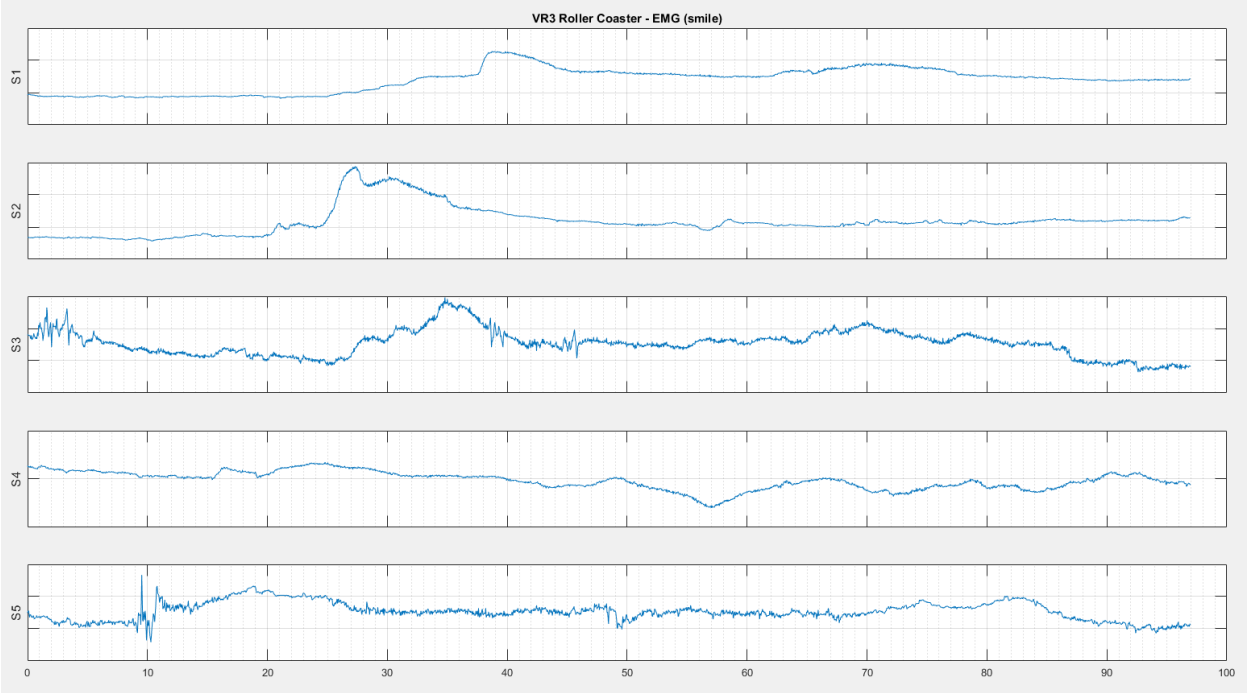


Figure 22: Subject EMG signal during Roller Coaster Segment

The EMG signal for S2 and S3 increases significantly at the point of the first drop however the DC component is less meaningful and needs to be filtered out.

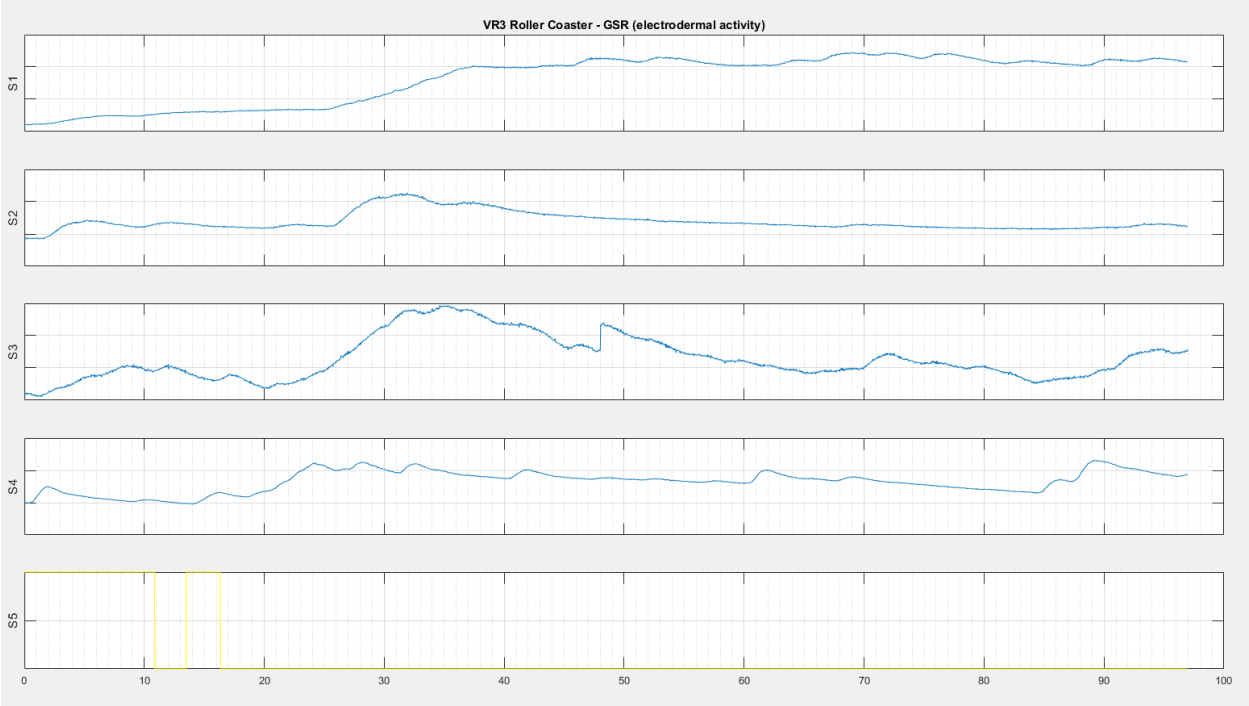


Figure 23: Subject Galvanic Skin Response signal during Roller Coaster Segment

The Galvanic Skin Response for all 4 Subjects increases about the time of the roller coaster reaching the top of the ramp and during the first drop. Unfortunately, Subject 5's electrode came loose and the data is invalid.

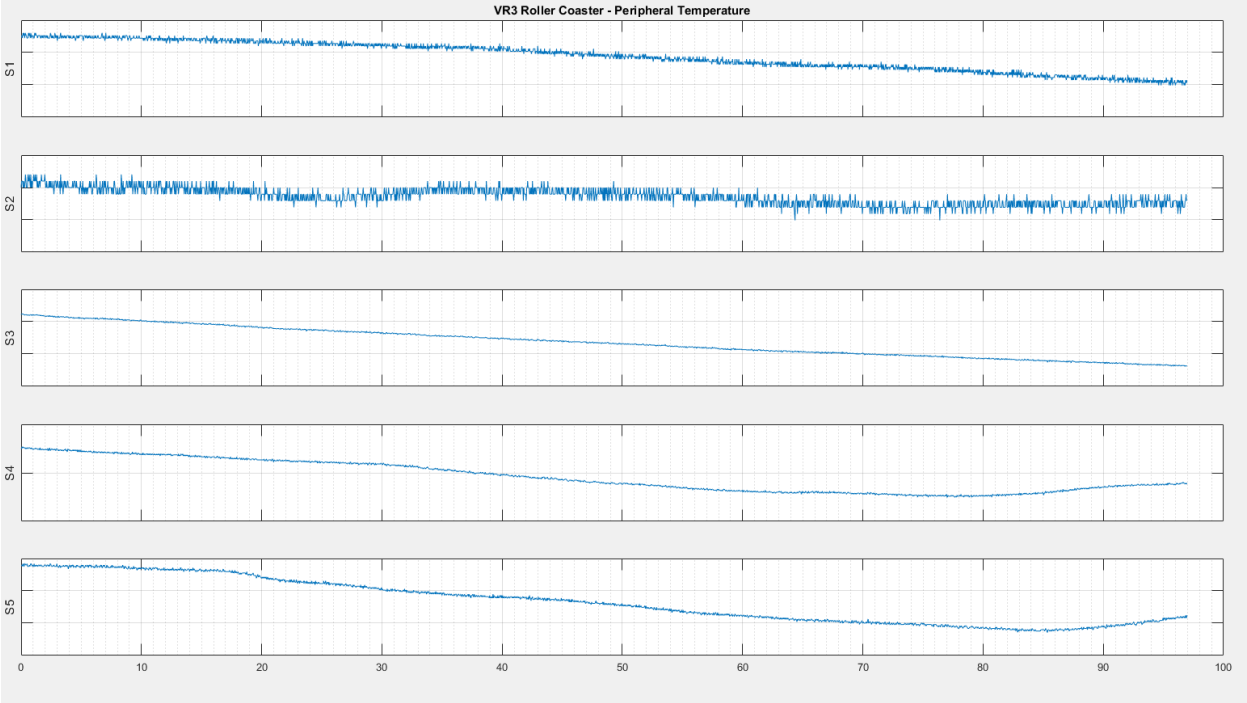


Figure 24: Subject Peripheral Skin Temperature during Roller Coaster Segment

The peripheral skin temperature for all subjects trended down during this session.

4.2.3 Pendulum Swing

This session was intended to cause height related anxiety. Subject 1 was the only participant who expressed a moderate fear of heights and consequently this segment was ranked pleasant and exciting by 4 of the 5 participants. The most significant event occurs at 57 seconds on the following graphs; it is when the participant is pushed off of the cliff in the virtual reality simulation.

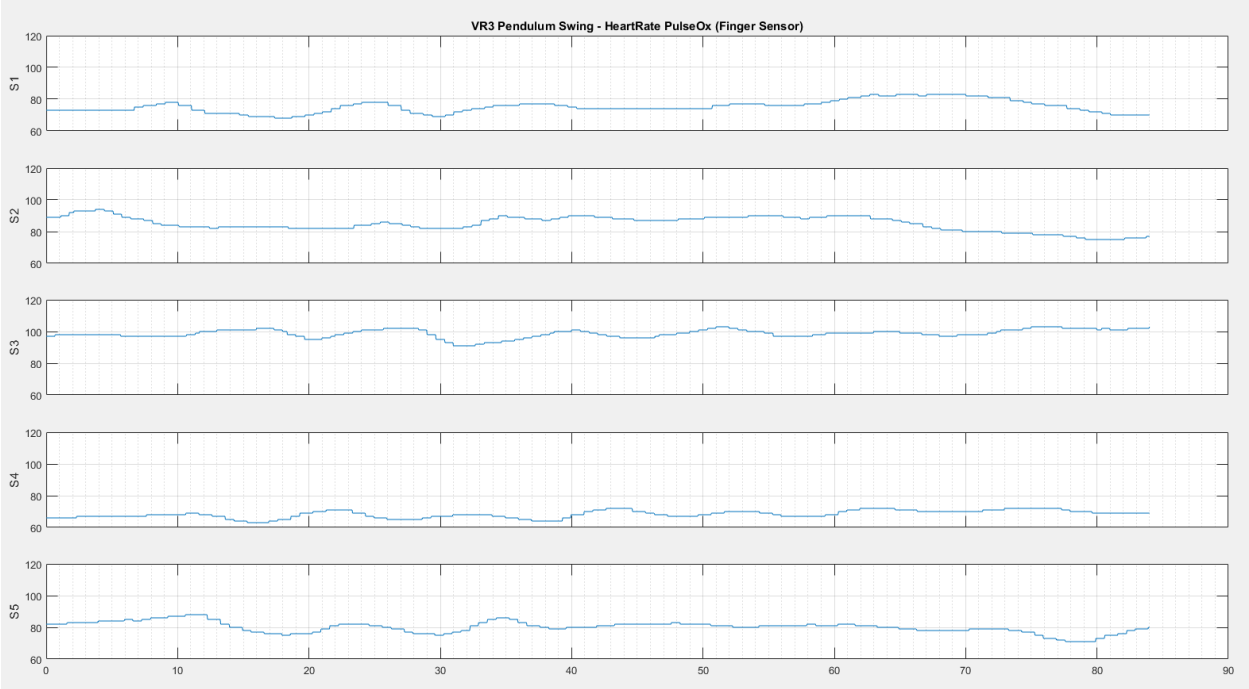


Figure 25: Subject Heart Rate during Pendulum Swing Segment

The heart rate of Subject 1 shows an increase following the "push" at 57 seconds. A very slight increase can also be seen in subjects 2, 3, and 4 with no meaningful change in Subject 5.

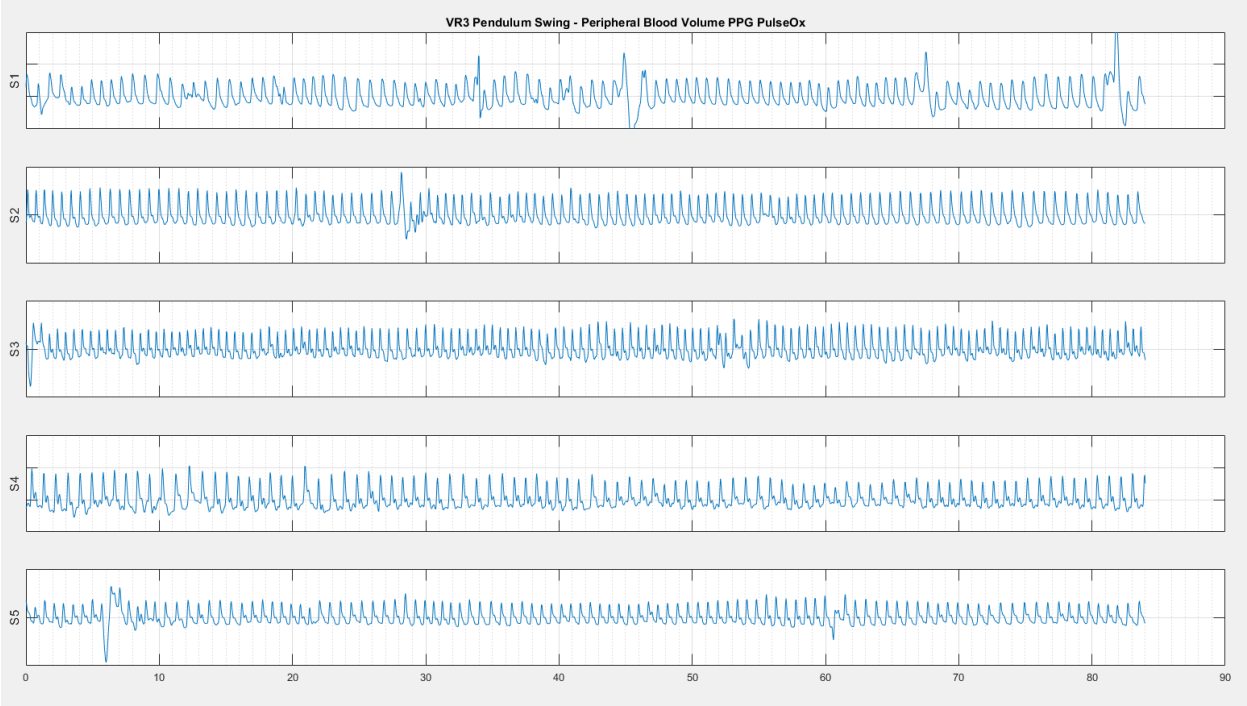


Figure 26: Subject Peripheral Blood Pulse Volume Pendulum Swing Segment

Peripheral blood pulse volume appears to decrease slightly in Subject 4 at the 57 second "push" point but no clear trend can be seen across all subjects.

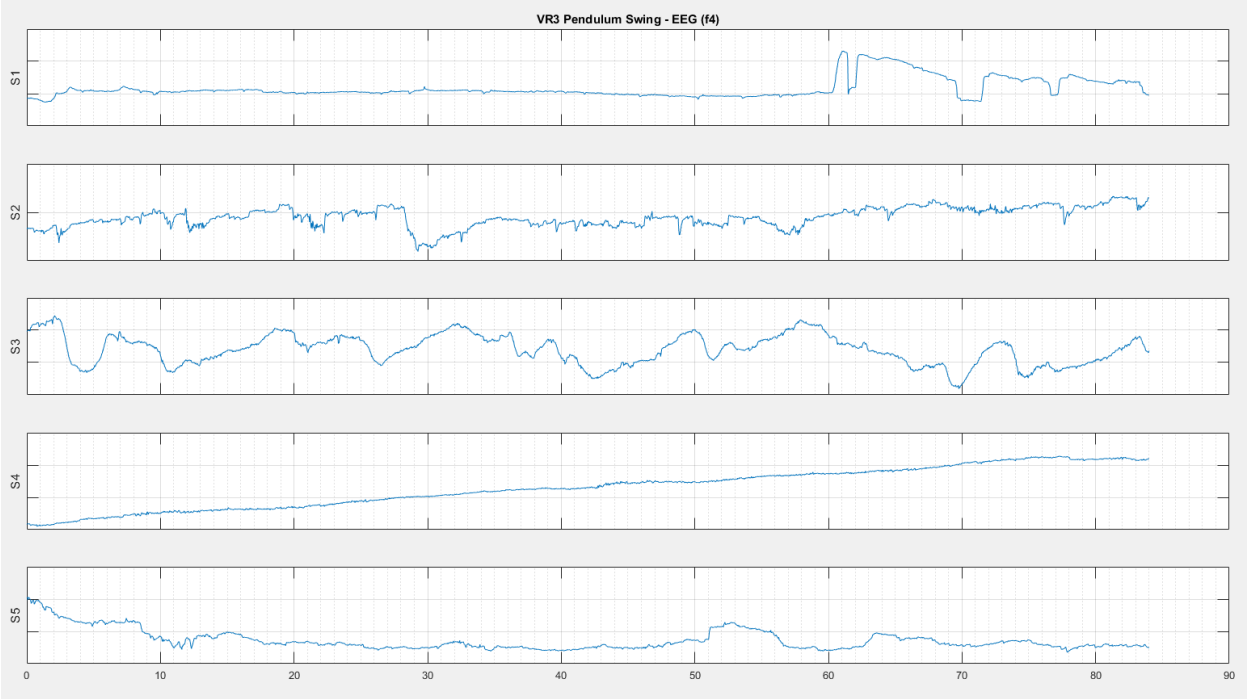


Figure 27: Subject EEG f4 during Pendulum Swing Segment

The promising rise in EEG f4 in Subject 1 previously discussed in Section 4.2 did not appear in any of the remaining four subject's EEG signal.

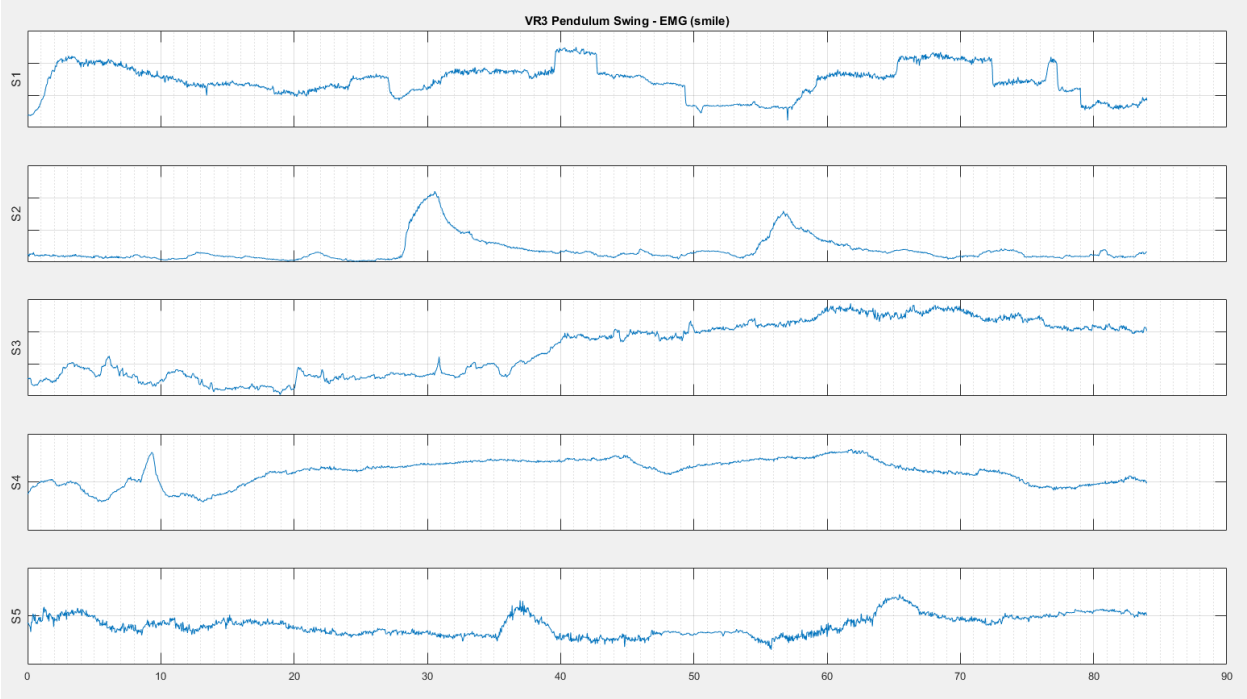


Figure 28: Subject EMG signal during Pendulum Swing Segment

The EMG signal charted here (auto-scaled) shows no specific markers at the 57 second "push" point. For Subject 1 there appeared to be an increase in EMG at this time as described in Section 3.3. That graph was also auto-scaled but across a much shorter time window. Further processing of the EMG signal to remove the low frequency DC voltage component is needed.

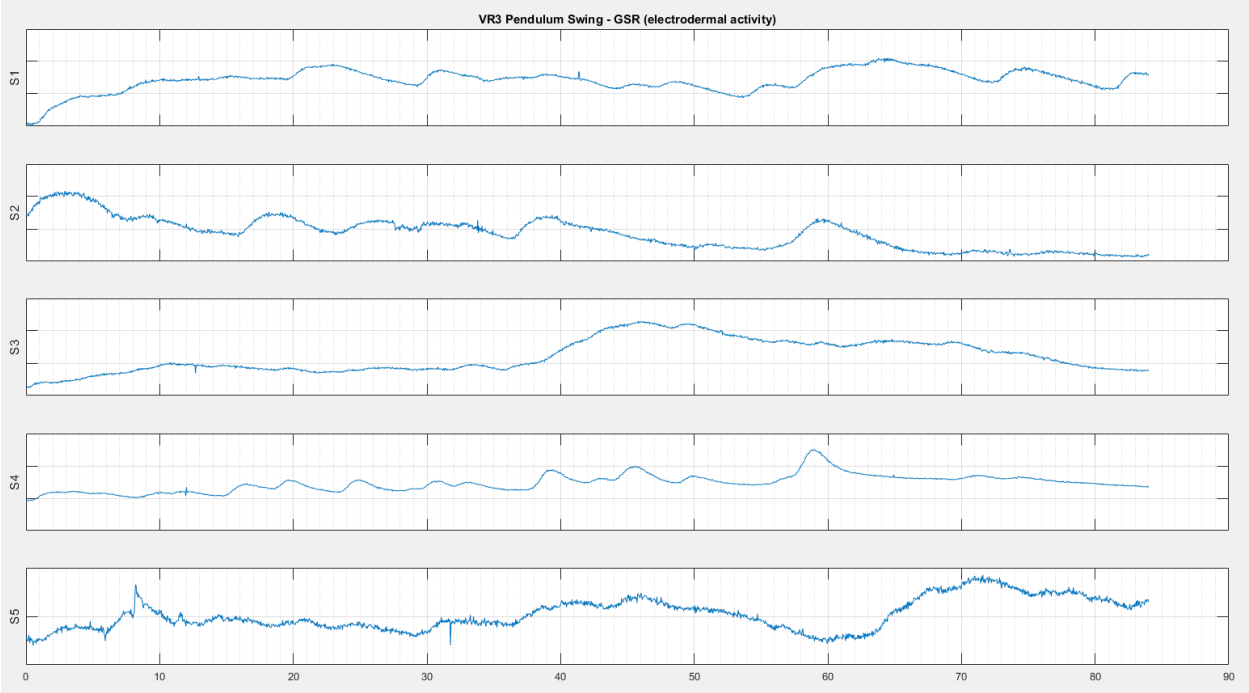


Figure 29: Subject Galvanic Skin Response signal during Pendulum Swing Segment

Subjects 2 and 4 seem to exhibit a galvanic skin response with a timing and that is consistent with the “push” at the 57 second point. However, no clear rise/fall is seen in Subjects 1, 3, and 5.

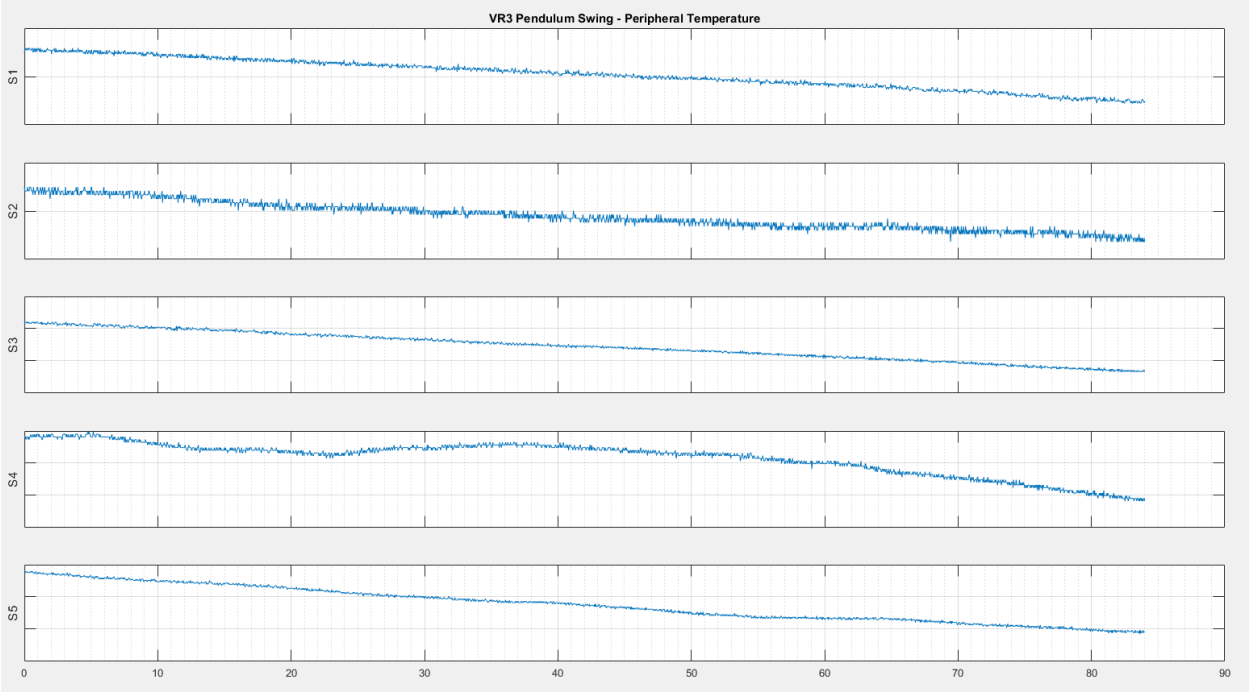


Figure 30: Subject Peripheral Skin Temperature Pendulum Swing Segment

The peripheral skin temperature for all subjects trended down during this session. There is no specific response at the 57 second "push" event. This segment was completed standing and it is possible that this had an impact causing the general downward trend in the peripheral skin temperature. Further investigation regarding the effect of sitting versus standing is warranted.

4.3 Feature Extraction and Segment Size

4.3.1 Simple Mean and Standard Deviation Feature Extraction

For initial quick analysis very simple mean and standard deviation features were extracted with a 1 second (250 sample) window. The resulting MATLAB table

contained 48 features, 2 for each of the 24 time based input signals. The response class was the session – in this case the relaxing VR2 and the exciting VR3 sessions.

The table was input in to the MATLAB classification tool [54] and all available classifiers were run and evaluated with 5-fold cross validation for a range of epoch sizes. While the accuracy is higher for a 1 second epoch this is likely due to overfitting as the physiological signals and emotional response will not very significantly in such a short time span. In addition, because data from all 5 subjects is used during the cross validation the results are much higher than found during hold-one-out analysis where the test set consists of the data from a subject who is not included in the training set.

Table 8: MATLAB Classifier Accuracy with 5 fold cross-validation, 1 second epoch, and mean + standard deviation features

Table 9: MATLAB Classifier Accuracy with 5 fold cross-validation, 5 second epoch, and mean + standard deviation features

1.1	Tree	Complex Tree	Accuracy: 93.5%	48/48 features
1.2	Tree	Medium Tree	Accuracy: 93.5%	48/48 features
1.3	Tree	Simple Tree	Accuracy: 86.2%	48/48 features
1.4	Linear Discriminant	Linear Discriminant	Accuracy: 73.1%	48/48 features
1.5	Quadratic Discriminant	Quadratic Discriminant	Accuracy: 69.8%	48/48 features
1.6	Logistic Regression	Logistic Regression	Accuracy: 88.4%	48/48 features
1.7	SVM	Linear SVM	Accuracy: 91.3%	48/48 features
1.8	SVM	Quadratic SVM	Accuracy: 93.5%	48/48 features
1.9	SVM	Cubic SVM	Accuracy: 93.5%	48/48 features
1.10	SVM	Fine Gaussian SVM	Accuracy: 84.7%	48/48 features
1.11	SVM	Medium Gaussian SVM	Accuracy: 89.1%	48/48 features
1.12	SVM	Coarse Gaussian SVM	Accuracy: 67.3%	48/48 features
1.13	KNN	Fine KNN	Accuracy: 85.5%	48/48 features
1.14	KNN	Medium KNN	Accuracy: 81.8%	48/48 features
1.15	KNN	Coarse KNN	Accuracy: 72.4%	48/48 features
1.16	KNN	Cosine KNN	Accuracy: 79.6%	48/48 features
1.17	KNN	Cubic KNN	Accuracy: 78.5%	48/48 features
1.18	KNN	Weighted KNN	Accuracy: 85.8%	48/48 features
1.19	Ensemble	Boosted Trees	Accuracy: 67.3%	48/48 features
1.20	Ensemble	Bagged Trees	Accuracy: **97.5%**	48/48 features
1.21	Ensemble	Subspace Discriminant	Accuracy: 93.1%	48/48 features
1.22	Ensemble	Subspace KNN	Accuracy: 93.5%	48/48 features
1.23	Ensemble	RUSBoosted Trees	Accuracy: 96.7%	48/48 features

4.3.2 Temporal and Frequency Based Feature Extraction

For second pass analysis utilized existing feature extraction algorithms that were developed for a previous sleep study also using physiological data. For each signal the 90 features shown in Table 10 were generated resulting in a total of 2160 feature vectors.

Table 10: List of Temporal and Frequency Based Features

nF.	Feature name
1	Average
2	Standard deviation
3-8	PSD- peaks frequency
9-14	PSD-peaks amplitude
15	Energy
16	Zero crossing rate
17	Energy entropy
18	Spectral centroid
19	Spectral spread
20	Spectral entropy
21	Spectral Rolloff point
22-26	MODWT- Energy of Wavelet coefficients
27-31	MODWT- Percentage of Energy of Wavelet coefficients
32-36	MODWT- Standard deviation of Wavelet coefficients
37-41	MODWT- Mean of Wavelet coefficients
42	Tsallis entropy
43	Renyi entropy
44	Shannon entropy
45-54	RSP of subbands
55	RSP- Slow wave bands-spectral bands Delta
56	RSP- Slow wave bands-spectral bands Theta
57	RSP- Slow wave bands-spectral bands Alpha
58-72	Harmonic parameters
73	Hjorth parameters– Activity
74	Hjorth parameters– Mobility
75	Hjorth parameters– Complexity
76	Skewness
77	Kurtosis
78-87	Autoregressive parameters
88-90	Percentile 25, 50, 75

4.3.3 Domain Specific Feature Extraction

For the final pass feature extraction algorithms were developed based on existing knowledge regarding the behavior of the physiological signals with respect to emotional response. Each of the 15 features were computed by subject and are described briefly below.

meanHR – the mean of the heart rate as reported by the pulse oximeter is calculated for each epoch and is normalized by subtracting the mean of the subject's heartrate for the entire dataset (the base heart rate)

magPPV – the magnitude of the peripheral blood volume as reported by the pulse oximeter was calculated for each epoch by subtracting the minimum value from the maximum value.

slopeGSR – the slope of the electrodermal activity (EDA) or skin resistance was calculated by subtracting the value of the last sample in the epoch from the value of the first sample in the epoch.

meanGSR – the mean value of the skin resistance was calculated as the average of all samples within each epoch.

slopePT – the slope of the peripheral skin temperature (SKT) was calculated for each epoch by subtracting the minimum value from the maximum value.

mECGHR – the mean heartrate based on the ECG signal was calculated by counting the number of peaks which were greater than 0.5 seconds apart during each epoch.

HRV – heart rate variability is a better predictor of emotion than raw heartrate [55]. The variability of the heart rate was computed by taking the maximum distance between adjacent peaks minus the minimum distance between adjacent peaks divided by the average distance between peaks for a given epoch.

minHRV – is calculated as HRV except the min peak distance only is used.

maxHRV – is calculated as HRV except the max peak distance only is used.

respA, respC – a similar peak counting method as mECGHR is applied with a 2 second peak to peak minimum for the abdomen and chest RIP signals.

respVA, respVC – the minimum peak to peak distance divided by the mean peak to peak distance is computed for each epoch from the abdomen and chest RIP signals.

meanfR – the mean value of the f4 EEG signal is computed. This signal is previously normalized by subject

magEMG – the magnitude of the EMG signal is calculated by subtracting the minimum value in the epoch from the maximum value in the epoch.

The results using this mix of features were better than those using the simple mean/standard deviation features and the temporal and frequency based features. The highest results were achieved via feature selection and will be discussed in the next two sections.

4.4 Feature Selection

4.4.1 Simple Mean and Standard Deviation Feature Selection

For the simple mean and standard deviation feature set only a few feature selection experiments were run. The accelerometer and gyroscope data from both the head and body radios were eliminated and did not significantly impact the results. Most of the feature selection efforts were on the large temporal and frequency based feature set and the smaller but varied domain based feature set which will be detailed in the next two sections.

4.4.2 Temporal and Frequency Based Feature Selection

Feature selection was performed on the 2160 features individually using a sparse technique as it was not possible to run feature selection on all features simultaneously.

The resulting 161 features identified were then again processed with a sparse technique resulting in 30 final features.

4.4.3 Domain Specific Feature Extraction

Multiple combinations of features were run during the development of the domain based features as well as some automated testing. The accuracy was found to be highest with the following set of features: meanHR, magPPV, slopeGSR, mECGHR, HRV. When each feature was evaluated individually the top 3 performing features were meanHR, magPPV, and HRV. With leave one out analysis the best results were achieved when the slopePT feature was removed. For a complete description of these features see section 4.3.3.

4.5 Classification Accuracy

As discussed earlier the classification accuracy results calculated using 5 fold cross-validation in the MATLAB Classification learner were much higher than leave on out by subject results. Given the small dataset and the goals of the research to be able to determine emotional response on new subjects the validation used for the following results was based on hold one out by subject. Specifically, for each subject a test set was built containing that subjects 24 time based signal data along with their reported arousal response. Given the limitations of the response data, valence was not used and arousal was classified as binary with 1 corresponding to an “exciting” response and a 0 corresponding to a “neutral” or “relaxing” response. The default MATLAB r2016a SVM classifier was used with a 10 second epoch.

For the simple mean and standard deviation feature set utilizing all 48 features (without feature selection) the hold one out accuracy was 74%. Using all 2160 temporal and frequency based features the hold one out accuracy was 57%. After feature selection to 30 total features the temporal and frequency based feature set hold one out accuracy was 72%.

The highest overall hold one out accuracy of 80% was achieved using a Support Vector Machine and the following five features: meanHR, magPPV, slopeGSR, mECGHR, HRV.

5 CONCLUSION

Experimental design is critical to the success of this research. Testing the stimuli and subject self-reporting responses prior to the more complex experiments with the full sensor setup would be beneficial. Unfortunately, this will likely require a much larger subject population as some level of desensitization will occur therefore it would be best to perform the data collection on subjects who have not previously participated in the virtual reality simulations. In order to better cover the relaxing portion of the arousal-valence space, calming or meditative segments should be added. More challenging will be the identification of emotionally unpleasant stimulus. Given the immersive nature of the virtual reality environment care must be taken not to cause undue stress with explicit or unsettling content. A thorough IRB review of the stimulus, subject selection, and procedures would be warranted with this type of content.

Much larger number of subjects with multiple runs are needed. Some physiological signals varied significantly between subjects with no universal telltale markers found. If possible, selecting subjects based on presence or absence of sensitivity to the intended stimuli would be beneficial. For example, a dataset with 50% of the subjects expressing a fear of heights and 50% having no fear of heights engaged in a virtual reality simulation that involves height and drop simulations would be very interesting.

In order to increase the number of subjects several elements will need to be improved. Less cumbersome equipment with better cable management and/or wireless sensors along with sensors built into headset or other wearable type garments instead of adhesive type electrodes would make the simulations much more pleasant and also

decrease the required setup time. Event marking should be as automated as possible. Video recording with remote audio capabilities was invaluable for this preliminary research but reviewing each video to determine event label start and stop points required a large amount of time. This manual technique also increases the risk of error and timing inaccuracies.

Feature extraction using both simple and complex techniques that were not domain specific did not yield robust results when tested on subject data not in the training set. Domain knowledge will likely need to be incorporated for each type of signal. For example, the rise and recovery of a GSR event is well documented and fairly easy to spot visually on a graph however specific feature extraction will be required to form a marker for this type of event in the feature table. In addition, motion is likely not relevant for the direct prediction of emotional response, however it could prove to be valuable in detecting and eliminating noise and motion related artifacts from the signals that are relevant.

With the continued progress in sensing technology and through the application of machine learning on large datasets, the classification of human emotion will help guide therapy, training, and the development of improved experiences with automated systems that include affective computing capabilities.

LITERATURE CITED

[1] E. Kaniusas, Biomedical Signals and Sensors I: Linking Physiological Phenomena and Biosignals, Heidelberg, Germany: Springer Verlag GmbH, 2012.

[2] R. W. Picard, Affective Computing, Cambridge: MIT Press, 1997.

[3] R. Ortner, E. Grunbacher and C. Guger, "State of the Art in Sensors, Signals and Signal Processing," Guger Technologies OG, Graz, Austria, 2013.

[4] M. J. Jamal, Signal acquisition using surface EMG and circuit design considerations for robotic prosthesis, INTECH Open Access Publisher, 2012.

[5] S. Day, Important factors in surface EMG measurement, Bortec Biomedical Ltd publishers, 2002.

[6] E. P. Scilingo, A. Gemignani, R. Paradiso, N. Taccini, B. Ghelarducci and D. De Rossi, "Performance evaluation of sensing fabrics for monitoring physiological and biomechanical variables," *IEEE Transactions on information technology in biomedicine 9.3,* pp. 345-352, 2005.

[7] C. Guger, G. Krausz, B. Allison and G. Edlinger, "Comparision of dry and gel based electrodes for P300 brain-computer interfaces," *Frontiers in Neuroscience,* pp. 1-6, 2012.

[8] S. Fairclough, "Physiological data must remain confidential," *Nature,* pp. 263-263, 2014.

[9] I. Korhonen, J. Parkka and M. Van Gils, "Health monitoring in the home of the

future," *IEEE Engineering in medicine and biology,* vol. 3, no. 22, pp. 66-73, 2003.

[10] G. Valenza and E. P. Scilingo, Autonomic nervous system dynamics for mood and emotional-state recognition: Significant advances in data acquisition, signal processing and classification, Switzerland: Springer International Publishing, 2014.

[11] L. Xiao, S. Boyd and S. Lall, "A scheme for robust distributed sensor fusion based on average consensus," *In IPSN 2005. Fourth International Symposium on Information Processing in Sensor Networks,* pp. 63-70, 2005.

[12] A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews),* vol. 1, no. 40, pp. 1-12, 2010.

[13] V. Kaarjakari, Practical MEMS: Design of microsystems, accelerometers, gyroscopes, RF MEMS, optical MEMS, and microfluidic systems, Las Vegas: Small Gear Publishing, 2009.

[14] N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury and A. Campbell, "A survey of mobile phone sensing," *IEEE Communications,* vol. 48, no. 9, pp. 140-150, 2010.

[15] Z. Xu, J. Hilton, G. Gates, S. Jelic, Y. Stern, M. Bartels, R. DeMeersman and R. Basner, "Increased sympathetic and decreased parasympathetic cardiovascular modulation in normal humans with acute sleep deprivation," *Journal of applied physiology,* vol. 6, no. 98, pp. 2024-2032, 2005.

[16] W. H. Spriggs, Essentials Of Polysomnography: A Training Guide and Reference

For Sleep Technicians 2nd Edition, Burlington: Jones & Bartlett Learning, 2015.

[17] P. &. F. W. V. Ekman, "Constants Across Cultures in the Face and Emotion," *Journal of Personality and Social Psychology, Vol 17(2),* pp. 124-129, 1971.

[18] E.-H. Jang, B.-J. Park, S.-H. Kim, M.-A. Chung, M.-S. Park and J.-H. Sohn, "Emotion Classification based on Bio-Signals: Emotion Recognition using Machine Learning Algorithms," *Proceeding of the 2014 International Conference on Information Science, Electronics and Electrical Engineering,* pp. 1373-1376, 2014.

[19] K. Gouizi, F. B. Reguig and C. Maaoui, "Emotion recognition from physiological signals," *Journal of medical engineering & technology,* Vols. 6-7, no. 35, pp. 300-307, 2011.

[20] P. Ekman, R. W. Levenson and W. V. Friesen, "Autonomic nervous system activity distinguishes among emotions," *Science,* pp. 1208-1210, 1983.

[21] P. Rainville, A. Bechara, N. Naqvi and A. R. Damasio, "Basic emotions are associated with distinct patterns of cardiorespiratory activity," *International Journal of Psychophysiology 61, no. 1,* pp. 5-18, 2006.

[22] C. Collet, E. Vernet-Maury, G. Delhomme and A. Dittmar, "Autonomic nervous system response patterns specificity to basic emotions," *Journal of the Autonomic Nervous System 62, no. 1-2,* pp. 45-57, 1997.

[23] F. Canento, A. Fred, H. Silva, H. Gamboa and A. Lourenco, "Multimodal biosignal sensor data handling for emotion recognition," *IEEE In Sensors,* pp. 647-650, 2011.

[24] R. W. Leon, I. Karacan and C. J. Hursch, Electroencephalography (EEG) of human

sleep: clinical applications, John Wiley & Sons, 1974.

[25] J. Sztajzel, "Heart rate variability: a noninvasive electrocardiographic method to measure the autonomic nervous system," *Swiss medical weekly,* no. 134, pp. 514-522, 2004.

[26] D. T. Lykken, "The GSR in the detection of guilt," *Journal of Applied Psychology,* vol. 43, no. 6, p. 385, 1959.

[27] J. Block, "A study of affective responsiveness in a lie-detection situation," *The Journal of Abnormal and Social Psychology,* vol. 1, no. 55, p. 11, 1957.

[28] J. T. Cacioppo, R. E. Petty, M. E. Losch and H. S. Kim, "Electromyographic activity over facial muscle regions can differentiate the valence and intensity of affective reactions," *Journal of personality and social psychology,* vol. 2, no. 50, p. 260, 1986.

[29] A. E. Kaufman, A. Bandopadhay and B. D. Shaviv, "An eye tracking computer user interface," *IEEE 1993 Symposium on Research Frontiers,* pp. 120-121, 1993.

[30] E. A. Kesinger, "Remembering emotional experiences: The contribution of valence and arousal," *Reviews in the Neurosciences,* vol. 4, no. 15, pp. 241-252, 2004.

[31] A. Gerrards-Hesse, K. Spies and F. Hesse, "Experimental Inductions of emotional states and their effectiveness: A review," *British Journal of Psychology,* pp. 55-78, 1994.

[32] A. Haag, S. Goronzy, P. Schaich and J. Williams, "Emotion recognition using bio-sensors: First steps towards an automatic system," *In Tutorial and research workshop on affective dialogue systems,* pp. 36-48, 2004.

[33] P. Lang, B. Cuthbert and M. Bradley, "International affective picture system (IAPS): Affective ratings of pictures and instruction manual. Technical Report A-8," University of Florida, Gainesville, FL, 2008.

[34] C. D. Katsis, N. Katertsidis, G. Gainiatsas and D. I. Fotiadis, "Toward Emotion Recognition in Car-Racing Drivers: A Biosignal Processing Approach," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, Vol. 38, no. 3,* pp. 502-512, 2008.

[35] R. L. Mandryk, M. S. Atkins and K. M. Inkpen, "A Continuous and Objective Evaluation of Emotional Experience with Interactive Play Environments," *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,* pp. 1027-1036, 2006.

[36] L. Mitchell, R. A. MacDonald and E. Brodie, "Temperature and the Cold Pressor Test," *The Journal of Pain,* pp. 233-238, 2004.

[37] C. Zong and M. Chetouani, "Hilbert-Huang Transform based Physiological Signals Analysis for Emotion Recognition," *Proceeding of the 9th IEEE International Symposium on Signal Processing and Information (ISSPIT),* p. 334 – 339, 2009.

[38] E. L. van den Broek, V. Lisy, J. H. Janssen, J. H. Westerink, M. H. Schut and K. Tuinenbreijer, "Affective Man-Machine Interface: Unveiling Human Emotions through Biosignals," *BIOSTEC 2009, Communications in Computer and Information Science (CCIS),* pp. 21-47, 2009.

[39] P. M. Agante and J. P. Marques De Sa, "ECG noise filtering using wavelets with soft-thresholding methods," *IEEE,* pp. 535-538, 1999.

[40] J. Goldie, C. McGregor and B. Murphy, "Determining levels of arousal using electrocardiography: a study of HRV during transcranial magnetic stimulation," *In 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, pp. 1198-1201, 2010.

[41] J. Bell, Machine Learning: Hands-On for Developers and Technical Professionals, Indianapolis: John Wiley and Sons, Inc, 2014.

[42] Y. S. Abu-Mostafa, M. Magdon-Ismail and H.-T. Lin, Learning from Data, AMLbook, 2012.

[43] G. Tsoumakas and I. Katakis, Multi-label classification: An overview, Thessaloniki: Dept. of Informatics, Aristotle University of Thessaloniki, 2006.

[44] L. Wang, Support vector machines: theory and applications, Vol 177, Spring Science and Business Media, 2005.

[45] T. Mitchell, "Artifical Neural Networks," *Machine Learning*, pp. 81-127, 1997.

[46] S. Nicu, I. Cohen, T. Gevers and T. S. Huang, "Multimodal approaches for emotion recognition: a survey," *International Society for Optics and Photonics*, pp. 56-67, 2005.

[47] T. S. Guzella and W. M. Caminhas, "A review of machine learning approaches to spam filtering," *Expert Systems with Applications*, vol. 7, no. 36, pp. 10206-10222, 2009.

[48] "Oculus Rift Applications," 15 September 2016. [Online]. Available: https://www.oculus.com/experiences/rift/.

[49] "BioRadio User Guide Rev E," 15 January 2016. [Online]. Available: https://glneurotech.com/bioradio/wp-content/uploads/2015/02/392-0050-Rev-E-BioRadio-User-Guide.pdf.

[50] P.-Y. Carry, P. Baconnier, A. Eberhard, P. Cotte and G. Benchetrit, "Evaluation of respiratory inductive plethysmography: accuracy for analysis of respiratory waveforms," *CHEST Journal*, vol. 4, no. 111, pp. 910-915, 1997.

[51] J. E. Sinex, "Pulse oximetry: principles and limitations," *The American journal of emergency medicine,* vol. 1, no. 17, pp. 59-66, 1999.

[52] "MATLAB Product Overview," 15 January 2016. [Online]. Available: https://www.mathworks.com/products/matlab/index.html.

[53] "Institutional Review Board," Texas State University, [Online]. Available: http://www.txstate.edu/research/orc/IRB-Resources.html. [Accessed 4 November 2016].

[54] "Signal Processing and Machine Learning Techniques for Sensor Data Analytics," MathWorks, 1 September 2015. [Online]. Available: https://www.mathworks.com/videos/signal-processing-and-machine-learning-techniques-for-sensor-data-analytics-107549.html. [Accessed 18 January 2016].

[55] R. Lane, K. McRae, E. Reiman, K. Chen, G. Ahern and J. Thayer, "Neural correlates of heart rate variability during emotion," *Neuroimage,* vol. 1, no. 44, pp. 213-222, 2009.

[56] X.-A. Fan, L.-X. Bi and Z.-L. Chen, "Using EEG to detect drivers' emotion with

Bayesian Networks," *Machine Learning and Cybernetics (ICMLC), vol. 3, IEEE,* pp. 1177-1181, 2010.

[57] H. Sim, W.-H. Lee and J.-Y. Kim, "A Study on Emotion Classification utilizing Bio-Signal (PPG, GSR, RESP)," *Advanced Science and Technology Letters, Vol. 87,* pp. 73-77, 2015.