Physiological Signal Analysis and Classification of Stress from Virtual Reality Video Game

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Abstract— **Stress can affect a person's performance and health positively and negatively. A lot of the relaxation methods have been suggested to reduce the amount of stress. This study used virtual reality (VR) video games to alleviate stress. Physiological signals captured from Electrocardiogram (ECG), galvanic skin response (GSR), and respiration (RESP) were used to determine if the subject was stressed or relaxed. Time and frequency domain features were then extracted to evaluate stress levels. Frequency domain methods such as low-frequency (LF), high-frequency (HF), LF-HF ratio (LF/HF) are considered the most effective for HRV analysis, Poincaré plots are more discerning visually and shares a 81% correlation with LF/HF ratio. GSR is associated with EDA activity, which only increases due to stress. Stress and relax were classified using Linear Discriminant Analysis (LDA), Decision Tree, Support Vector machine (SVM), Gradient Boost (GB), and Naive Bayes. GB performed the best with an accuracy of 85% after 5 fold cross validation with 100 iterations, which is admirable from a small dataset with 50 samples.**

I. Introduction

According to the American Psychology Association 2014 report, 75% of Americans report experiencing at least one symptom of stress within a month [1]. Stress is associated with many human activities such as our jobs, relationships and finance. It affects a person's immune response and causes several health problems [2].

On the other hand, eustress can have a positive effect on human physiology. It can help an individual focus and feel energized, allowing a person to perform at their peak level. This is due to the blood vessels dilating which increases blood flow to the brain, muscles and limbs [3].

A person's mental, physical and emotional response due to stress is continuously adjusted to counter the stress introduced. Continuous resist to stress transitions the body into its second resistance state, and once resist is exhausted, a person becomes distressed [4]. The blood vessels constrict during distress, resulting in a person transitioning to a state of rage, impairing their cognitive function and physical health. Early detection of stress along with established methods to better manage stress can impact the health of millions of people around the world and reduce the risk of major cardiovascular diseases such as hypertension, diabetes, myocardial infarction. [5], [6], [7].

The purpose of this experiment was to analyze physiological function associated with increased and decreased levels of stress from VR simulations and a cognitive game. These simulations include VR roller coaster, color stroop test and a novel VR fish game developed by Shaftesbury. The physiological signals such as ECG, GSR, and RESP signals, were acquired through CAPTIV wireless sensors. The experiment explores whether the VR video game is a valid solution to manage stress and prevent distress. The findings of the study can help develop apps, games and algorithms to improve the health of others through entertainment.

Section II provided a high level literature review on video game related stress analysis. Section III summarized the dataset and the methodology. Section IV provided the experiment results followed by conclusions and discussion in Section V.

II. Literature Review

Stress is associated with many situations as indicated by Rosenberg et al. [8], whether it is a conference presentation, medical emergency, period of pain, exercise, math, rest, mental stress test or meditation, depending on the activity low-high level of stress is connected to a certain level. Salahuddin and other scientists have shown that HRV of ECG can be used to discriminate mental stress stage [9]. Boonnithi et al. shown that other ECG features such as LF and HF are also effective [10]. Rosenberg et al. used 2D scatter plots of LF vs. HF for stress assessment from different scenarios such as performing mathematics calculations, under pain, in an emergency, giving a presentation, and doing meditation [8]. The results concluded that 2D scatter plots were much more efficient than 1D univariate method, which produced an accuracy of 90% or above, whereas 1D resulted in only 70%. Bu etl al. studied the correlation between nonlinear Poincaré plots and LF/HF ratio for mental stress [11]. We utilized Poincaré plots to examine stress ensuing a VR video game phase. Poincaré has been used in HRV analysis as early as 2006 [12]. Abdi et al. revealed that chronic stress reduces the reaction of ANS activity in response to cognitive load, which significantly increases SNS activity and decreases PNS activity due to increased stress [3]. Cho et al. conducted an experiment to understand the relationship between stress levels and skin temperature. The experiment required the use of wearable photoplethysmography (PPG), GSR and ECG sensors to detect changes in blood volume within the peripheral blood vessel, cardiac activity, level of skin conductance through electrodermal activity (EDA), skin temperature through EDA, and HRV using ECG [13]. Javorka et al. determined that respiration rate increases in response to increased stress [14]. Aliary et al. studied the beneficial

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and harmful effects of video games on cognitive functions. They analyzed the function of alpha-amylase, cortisol, and brain waves due to stress using Electroencephalogram (EEG) signals [15]. The results indicate that depending on the type of video games, stress level varies as well. Non violent games which can stimulate mental activity such as tetris are beneficial for stress levels.

Table I presents other results of binary classification for stress. Schimdt el al. bridged the gap between affective emotion and stress. He evinced the impact of emotions on stress development with 93% accuracy using Adaboost (AB) [16]. Hosseini et al. studied emotional stress by utilizing EEG [17] with 82.7% accuracy using neural network Elman classifier. Saidatul et al. detected mental stress through EEG and classified with 91.7% accuracy using neural network (NN) [18]. Khosrowabadi et al. studied mental stress during exams by detecting EEG signals with 90% accuracy using K nearest neighbors (KNN) [19]. Sharma et al. studied the effect of videos on stress levels using ECG, skin temperature (ST), blood pressure (BP), eye gaze, pupil, and EEG with 95% accuracy using SVM [20]. Fares el al. analyzed multiple levels of mental stress with 94.79% accuracy using SVM [21]. Arsalan studied perceived mental stress through EEG signals with 92.85% accuracy using multilayer perceptron (MLP) [22].

TABLE I
RELATED STRESS STUDIES USING BINARY CLASSIFIERS, BUT NOT USING VIRTUAL REALITY GAMES.

Ref	Signal	Method	Acc	Purpose
[16]	ECG, EDA, EMG, BVP, RESP	LDA, AB	93%	Stress due to effective emotion
[17]	RESP, SK, HRV, PPG	NN	83%	Emotional stress
[18]	EEG	NN, Burg, Yule, Welch	92%	Mental stress
[19]	EEG	KNN, SVM	90%	Exam stress
[20]	ECG, ST, BP, eye gaze, pupil, EEG	SVM, ANN	95%	Stress from videos
[21]	EEG	SVM+ ECOC	95%	Multilevel mental stress
[22]	EEG	MLP, SVM, NB	93%	Perceived mental stress

III. DATASET AND METHOD

In order to understand various physiological functions associated with stress, 3 types of physiological signals (ECG, GSR, Respiration) were collected from each subject. The data acquisition protocol was approved by the research ethics board of Ryerson University. The experiment was broken down into 4 phases: (T1) baseline phase - relax phase, (T2) roller coaster phase - stress phase, (T3) colour stroop test - stress phase, and (T4) VR fish game - relax phase. The initial phase (T1) was used to measure their baseline/normal parameters while relax. Phases T2 and T3 consisted of a roller coaster VR simulation and cognitive game in order to induce stress through negative emotions and cognitive load. The last phase (T4) consisted of a VR fishing game which was a biofeedback game to relax the subjects and return their physiological function back to normal after the induced stress.

A. Dataset

There were 14 subjects who participated in the study, aged between 20-40 years old. Three different physiological signals were measured from each subject for 4 phases, which resulted in 166 ((3 signals * 4 phases * 14 subjects) - 2 bad signals) signals, which is less than the expected 168 signals but one subject felt over stressed to continue with the roller coaster phase and another signal was not detected due to technical error associated with wireless transmission of the signal data via Bluetooth. Overall, 21 sets of signals were captured from the stress phases and 29 from the relax phases.

Each set of signals contains ECG, GSR and RESP signals. The wireless ECG sensor sampled at 250 Hz was placed around the subjects thorax, the RESP sensor sampled at 32 Hz was placed around the abdomen, two electrodes from the GSR sensor sampled at 32 Hz was placed on two fingertips of the subjects opposite hand. Each sensor was integrated with two electrodes embedded within the belt. The sensors are capable of detecting and producing high quality signals with fewer electrodes, making it easier for the subject to conduct the experiment.

B. Method

All signal has gone through the preprocessing. The R-R peak detection was performed on ECG signals to extract most of the time domain features. These ECG time domain features were used to extract the frequency domain features. Both time domain and frequency domain features fed into the five different classifier to compare classification accuracy.

1) Preprocessing: For ECG signals, various digital filters were used to remove baseline wander, motion artifact, and interference from the power line. Daubechies 6 Wavelet of order 10 was then applied to smooth the filtered signals. A butterworth filter lowpass filter of order 6 with a cutoff frequency at 0.5 Hz was used to preprocessing GSR signal. A Blackman bandpass filter with a bandpass frequency of 0.5-35 Hz was used to preprocess the respiration signal [23].

2) Feature Extraction: Time domain features were extracted from the physiological signals. From the time domain features, frequency domain features were then extracted. TABLE II and TABLE III present a list of the various features and their description[24]. Time domain variables were measured from ECG parameters, R-R variation for one R-interval to the next was utilized to assess R-R variability, HRV, nonlinear standard deviation SD1, SD2, approximate entropy (ApEn) and Poincaré plot. The time domain R-R interval variation was interpolated (cubic interpolation) to smoothen the signal, fit estimates for errors associated, provide an evenly sampled signal and transformed into power spectral density through AR (pyulear) method and Lomb scargle

TABLE II
TIME DOMAIN FEATURES

Features	Signal	Description
HR	ECG	The rate of change associated with R-R intervals from HR represents HRV. Increases due to stress
SDNN	ECG	The standard deviation of interval between two normal heartbeats (NN). NN measures the total power. Decreases in response to stress. $SDNN = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(RR_j - \overline{RR})^2}$
RMSSD	ECG	The root mean square of successive differences between normal heartbeats. Primarily manipulated by PNS activity. $RMSSD = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(RR_{j+1} - \overline{RR_j})^2}$
pNN50	ECG	Represents the percentage of the difference associated with NN interval which differ more than 50 ms.It shares a strong correlation with PNS activity, RMSSD, HF
SD1	ECG	Non-linear variables derived from the Poincaré plot. Shares a high correlation with HF, RMSSD. Decreases due to stress
SD2	ECG	Non-linear variables derived from the Poincaré plot. Shares a high correlation with LF. Increases in response to stress
ApEN	ECG	Represents the ratio between SD2 and SD1. Shares a high correlation with LF/HF. Increases due to stress
GSR std	GSR	Standard deviation associated with electrodermal activity. Increases during stress
GSR mean	GSR	Mean value obtained from measuring the rate of change associated with EDA activity. Increases during stress
Resp Rate	RESP	Represents breathing rate, increase in Resp rate leads to increased PNS activity, HF and decreased LF, SNS activity. Increases in response to stress

periodogram (plomb) to delineate frequency domain variables associated with HRV. In order to discriminate between stressed and relaxed subject, their physiological parameter was compared with their baseline data. An increased LF, decreased HF, increased heart rate (HR), increased LF/HF, reduced HRV and decreased percent of adjacent R-R interval differing by more than 50ms (PNN50) was associated with an increase in stress levels. Respiration signal was processed through a notch filter and an increase in breathing rate was associated with an increase in stress levels. GSR was filtered using a low pass filter (LPF) and the variations were analyzed using 30 s windows. It is used to indicate EDA activity, which measures the dynamic skin temperature associated with sweating and an increased GSR indicated an increase in stress levels.

3) Classification: The level of stress induced within each subject varied anywhere from low/normal stress level to high level of stress. In this study, we used five very assimilar binary classifiers to determine stress and relax conditions. These five classifiers were Linear Discriminant Analysis (LDA), non-parametric based Decision Tree (DT), Gaussian kernel based Support Vector Machine (SVM-RBF) with gamma derived from the variance of the data, ensemble-based Gradient Boosting (GB), and Naive Bayes (NB) using a Gaussian density function to model the data.

TABLE III
FREQUENCY DOMAIN FEATURES

Features	Description
VLF	Represented within the VLF band (0.0033-0.04 Hz) and it is mediated by SNS activity
LF	Represented through 0.04-0.15 Hz within the PSD, it is mostly used to indicate SNS activity but can specify PNS activity
HF	Represented by the frequency range of 0.15-0.40 Hz and solely indicates PNS activity
LF/HF	Represents ANS activity, increases in response to increased stress and decreased HRV

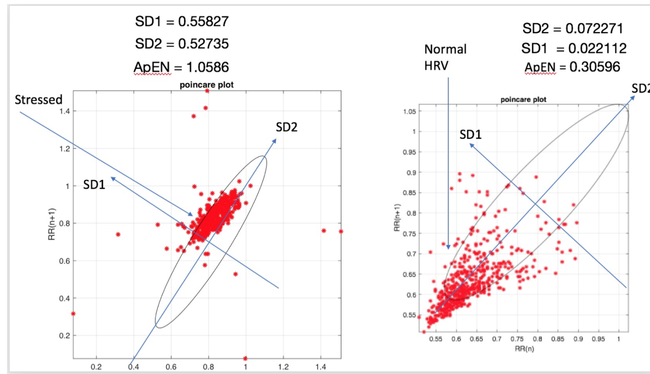

Fig. 1. Poincaré plots used to discriminate between stress and normal

IV. RESULTS

Fig. 1 represents a Poincaré plot for stress and normal subjects. A normal state resulted in a SD1 of 0.022, SD2 of 0.072 and ApEN of 0.306. Stress resulted in a SD1 of 0.558, SD2 of 0.527 and ApEN of 1.06.

Fig. 2 indicates that under stressed condition, there was an obvious increase in LF (0.04-0.15 Hz) and reduction in HF (0.15-0.4 Hz) as shown in subplot (a). While the subject is relaxed, the LF tends to be lower and there was an increase in HF as depicted in subplot (b). Which is indicative of increased HRV and PNS dominance.

Results obtained demonstrates that the VR game did indeed reduce stress levels. It resulted in a reduction in HR from 76.05 bpm to 74.22 bpm, reduced ApEN from 0.875 to 0.757, reduced LF from 2.692×10^3 ms^2/Hz to 2.3397×10^3 ms^2/Hz, HF increased from 1.49×10^3 ms^2/Hz to 2.65×10^3 ms^2/Hz, LF/HF ratio reduced from 1.8019 to 0.882 and GSR_{mean} reduced from 5.665 to 3.257.

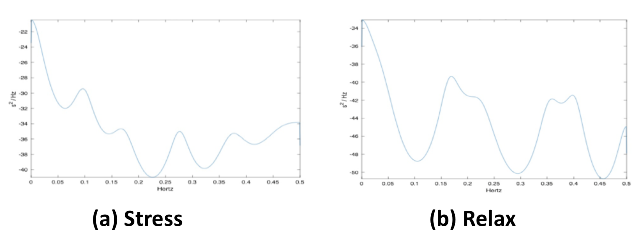

Fig. 2. AR PSD discriminating between stress and relax

TABLE IV
CLASSIFICATION RESULTS

	Accuacy	Precision	Recall	AUC-ROC
LDA	0.67±0.10	0.68±0.14	0.65±0.14	0.65±0.12
DT	0.72±0.17	0.73±0.18	0.72±0.18	0.72±0.18
SVM-RBF	0.76±0.12	0.80±0.12	0.74±0.12	0.74±0.12
GB(100)	**0.85±0.14**	**0.86±0.14**	**0.85±0.14**	**0.85±0.14**
NB	0.64±0.15	0.66±0.19	0.68±0.19	0.60±0.14

From the results, it is evident that the video game was a great distraction from stress and it can increase PNS activity which leads to a more relaxed state.

The classification results provide in TABLE IV were obtained using 5-fold cross-validation with 100 iterations. The dataset was split into 80% for training and 20% for validation. The obtained performance metrics are provided in Table 2. Four performance metrics composed of accuracy, precision, recall, and area under the Receiver Operating Characteristics curve (AUC-ROC) were used to compare the results. The ensemble-based Gradient Boost with a fixed size of 100 trees out-perform the other classifiers, followed by SVM-RBF. With such as small dataset, NB performed the worst since the density function of the dataset cannot be truly extracted. LDA also performed poorly, but the algorithm provided collinear relationship between features. This indicated that feature dimension reduction can provide better insights in future research.

V. Conclusions and Discussion

The purpose of this research study was to verify the impact of the VR fish game, it was developed by Shaftesbury to manage stress and anxiety. The results indicated that the video game can change a person to a more relaxed state. Using 100 iterations of 5-fold cross-validation, gradient boost (GB) with 100 trees provided an accuracy of automated classification of 85%.

In the future, we will consider multi-level classification such that more granule classification of stress can be automatically estimated. Deep learning methods are effective for automatic classification of stress but a considerably larger dataset would be required to classify stress more accurately.

VI. Acknowledgement

The authors would like to thank NSERC for funding the project, Shaftesbury for providing the VR bubble bloom fish game and Intel[1] for supporting the project and providing the PC Dev Kit.

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