Emotional State Classification in Virtual Reality Using Wearable Electroencephalography

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Abstract. This paper presents the classification of emotions on EEG signals. One of the key issues in this research is the lack of mental classification using VR as the medium to stimulate emotion. The approach towards this research is by using K-nearest neighbor (KNN) and Support Vector Machine (SVM). Firstly, each of the participant will be required to wear the EEG headset and recording their brainwaves when they are immersed inside the VR. The data points are then marked if they showed any physical signs of emotion or by observing the brainwave pattern. Secondly, the data will then be tested and trained with KNN and SVM algorithms. The accuracy achieved from both methods were approximately 82% throughout the brainwave spectrum (α, β, γ, δ, θ). These methods showed promising results and will be further enhanced using other machine learning approaches in VR stimulus.

1. Introduction

Virtual Reality (VR) has been on the rise for every industry especially in the smartphone industry where they want to capitalize this feature. Oculus, HTC Vive and Samsung Gear are some of the notable industries competing in the VR field. Some of the notable features of using VR from applications are such as gaming and 360 videos that allows people to see and observe what other people have recorded throughout the journey and their surrounding environments.

In many of the demos from the companies that have conducted with VR, the participants would be immersed into the VR and demonstrated body movements and emotions that showed signs of fear such as riding a roller coaster and losing their sense of ground due to cognitive manipulation. However, there were not any application that have the adaptivity to capitalize the mental state of the user that could help the user which would then improve the user’s experience inside the VR world.

The mental state of the user which is an ongoing electrical activity of the brain, particularly known as electroencephalography (EEG) which shows the ongoing sensory such as motor movements,
emotions and memories. This would provide an indication of the level of engagement for the user immersing into the VR which could be measured and quantified.

There are numerous researchers who have conducted in neuroinformatic to obtain the brainwave signals from humans. However, none has ever approached with the method of classifying mental state of users using VR as the stimulus. Technology has evolved throughout the years and EEG equipment have scaled down and are easily accessible by public to obtain.

In this research, we will be using the Muse headband which was developed by Interaxon for recording of the brainwave activity happening within the user’s brain when they are immersed into the VR. The approach for this research will require the user to not have any motion sickness and impaired eyes. With the data obtained from the brainwave, the data will then be filtered with KNN and SVM obtained from the brainwave such as muscle movements and eye twitches using R language data analysis. They will then be tested and trained with Machine Learning Language to identify emotional brainwave patterns to allow adaptive interaction between VR and the current user’s mental state.

This review paper will be divided into 5 sections. Firstly, the background and related work for this research paper will be briefed. Secondly, the methodology of this research. Thirdly, the results and data analysis. Fourth, the analysis of the results will be discussed. Lastly, the conclusion and future work will be presented in this section.

2. Background and Related Work
In this section, we will brief through the method and the approach of this research.

2.1. Virtual Reality Immersion
A software was developed and used to obtain the current brain’s state of concentration or relaxation in real time [1]. The software uses a plane to be controlled by the user and will move according to the mental state whereby if the user concentrates, the plane will move up, relaxation will move the plane downwards. There were also other simulation such as a driving simulation where the approach of this was to observe the mental state of the user such as boredom and fatigue if they were given a repetitive tasks [2]. Lastly, a group of participants were tasked to solve problems given to them and to differentiate each task for their level of difficulty [3].

2.2. Mental State Classification
Researchers had conducted different approaches to classify the mental state of the brain signals. Methods include electroencephalogram (EOG), electrocorticography (ECoG) and functional magnetic resonance (fMRI). However, electroencephalography (EEG) has a larger network of information stored within the brainwave which could provide responses towards the emotional state of the user [4]. Affective Computing (AC) was developed to identify and classify the emotional state of the user by measuring the behavioural and physiological signals [5].

2.3. KNN and SVM
There are several researches conducting data analysis on EEG with some of the commonly used methods such as K-nearest Neighbor (KNN) and Support Vector Machine (SVM). In some cases, researchers [6, 7, 8, 9] reported that they achieved an average accuracy of 70% and above using the mentioned methods to classify their user’s mental state.
2.4. EEG

Most EEG devices that were used in the process of obtaining the brainwave signal were mostly laboratory grade hardware and were very costly in obtaining these devices. These devices are mostly kept by organizations which were difficult to get an appointment and the devices are not portable to be brought out from the premise for experimentation purposes. Therefore, there was a need to approach this problem and Interaxon has developed a portable and small headband known as Muse for consumers to obtain. Most researchers [1, 10, 11, 12, 13] used this convenient headband to obtain their brainwave signals for their research thanks to its low-cost production even though it suffers from the lower quality of signal acquisition.

3. Research Methodology

Ten (2 Female, 8 Male) participants were recruited from various backgrounds aged between 22 through 65 who were residing in Kota Kinabalu, Sabah, Malaysia. The participants had no prior brain damage or mental disorder with little to no motion sickness. Each participant were asked to wear a VR Box headset together with a pair of earphones and a smartphone device along with the Muse Headband. The participant were then asked to play a VR app that was downloaded from the Google App Store.

The participants were asked to explore the VR by observing the surrounding areas of the VR. During the exploration inside the VR, any external stimulus was taken with great care from interfering the participants unless the participant showed any signs of mental fatigue that would be deemed dangerous to continue. The EEG readings were recorded from the Muse headband with the assistance of a third-party app known as Muse Monitor obtained from Google App Store developed by James Clutterback. The positions of where the Muse will collect the data are indicated with the head points from TP9, AF7, AF8, TP10 and reference point at FPz.

The collected data will then be analyzed using both KNN and SVM methods to classify the mental state of the participants and train the models to be able to identify and recognize the brainwave patterns and evaluate its performance on the analysis.

4. Result and Data Analysis

The format of the data recorded was using comma-separated-value (CSV) for use in R programming. The recorded data includes absolute values from different bands with different electrodes performing Fast-Fourier Transform (FFT) from the raw data obtained, raw signal from different electrodes and the horse-shoe indicator (the sensor connectivity to the human skin from the electrode) with marker buttons. The table displaying the data that was obtained from the Muse Monitor application is shown in table 4.0. The original signal from the RAW brainwave of the participant is shown in figure 4.0.
Table 4.0 The data that was recorded from Muse Monitor Application

| Time  | Delta   | Theta  | Alpha  | Beta    | Gamma   | Delta   | Theta  | Alpha  | Beta    | Gamma   | Merging  |
|-------|---------|--------|--------|---------|---------|---------|--------|--------|---------|---------|----------|
| 10:12 | 0.01234 | 0.0032 | 0.0234 | 0.0032  | 0.01234 | 0.01234 | 0.0032 | 0.0234 | 0.0032  | 0.01234 | 0.01234  |

The data is then rearranged to feed the data classifier and was saved in a different filename to avoid any changes to the original data which will be required for future references. The band of interest: alpha, beta, delta, gamma and theta. A length of 20 data points (approximately 1 data point for every 0.5 seconds) was selected before and after the marker was pressed to highlight the significant events that displayed physical emotional changes such as the doll that made a jump scare or any creepy motions that was displayed within the room. Resting state data points was selected from the data points before the subject was subjected to any stimulations.
Table 4.1 Adjustment of data to be fed into the classifier

| Participant Id | Raw Brainwave Signal Data | Adjusted Data |
|----------------|---------------------------|--------------|
| A              |                          |              |
| B              |                          |              |
| C              |                          |              |
| D              |                          |              |
| E              |                          |              |

However, a few participants were not explicitly displaying their emotions physically during the recording session and it is difficult to establish a marker on the data point in the timestamp. The raw brainwave signal data was then used to analyze and was marked according to the highest peak value of the signal in Y-axis and the approximate time where the participants would be stimulated during the session.

The datasets are then selected for a number of rows to be trained and a number of rows to be tested for the evaluation of the performance with KNN and SVM. Table 4.2 shows the selected datasets for training and table 4.3 shows the selected datasets to be tested for the performance evaluation.

Table 4.2 Datasets which are Selected to be Trained

| Dataset Id | Data Sets Selected |
|------------|--------------------|
| 1          |                    |
| 2          |                    |
| 3          |                    |
| 4          |                    |
| 5          |                    |

Table 4.3 Datasets which are Selected to be Tested

| Dataset Id | Data Sets Selected |
|------------|--------------------|
| 1          |                    |
| 2          |                    |
| 3          |                    |
| 4          |                    |
| 5          |                    |
Table 4.3 Dataset which are selected to be Tested for the Accuracy Prediction

| Participant | Dataset (x) | Dataset (y) | Dataset (z) | Dataset (α) | Dataset (θ) | Dataset (γ) | Dataset (%) | SVM (%) |
|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|---------|
| A           | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 85.48       | 85.48   |
| B           | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 85.48       | 85.48   |
| C           | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 85.48       | 85.48   |
| D           | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 85.48       | 85.48   |
| E           | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 85.48       | 85.48   |
| F           | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 85.48       | 85.48   |
| G           | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 85.48       | 85.48   |
| H           | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 85.48       | 85.48   |
| I           | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 0.23456789  | 0.12345678  | 85.48       | 85.48   |

The data obtained from the Muse Monitor were then trained and tested using KNN and SVM and the accuracy percentage of the algorithm were tabulated as shown in table 4.2.

Table 4.4 The Accuracy of Each Participant using KNN and SVM methods to train and test the observed brainwave patterns.

| Participants | KNN(%) | SVM(%) |
|--------------|--------|--------|
| A            | 76.54  | 76.54  |
| B            | 85.48  | 85.48  |
| C            | 82.91  | 83.42  |
| D            | 91.29  | 91.42  |
| E            | 60.98  | 60.98  |
| F            | 69.70  | 68.94  |
| G            | 95.94  | 95.94  |
| H            | 92.98  | 92.98  |
| I            | 86.16  | 86.16  |

5. Conclusion
The data analysis showed promising results in classifying he mental state of the participants while immersed under VR. This would provide a foundation for reference point as VR has never been conducted with EEG and would prove useful for future developments.

For future recommendations, the number of participants will be increased to 30 to be able to obtain a better convincing data on the accuracy of the mental classification. There were also a need to change the VR to provide a deeper impact for the participant. However, this will require further reconsideration as the app that was experimented with may traumatize other future participants.

There is also the difficulty of setting up a proper environment for the participant to fully immerse into the VR as not all participant were available to travel to the vicinity of the experiment that was conducted. Instead, we have to arrange logistics to travel to their premise and or using an empty ground area to conduct the experiment while the surrounding environment was dark and quiet. All necessary steps to avoid external stimulus were reassured before the conduct of the research.
Muse headband was not able to fit into most subjects even when the participants were in their teens (female aged 17), when fitted with the rest of the headgears to record the data. A consideration on the head size will be required to evaluate so that future experimentation would ease with the minimal requirement of the head size.

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