EEG-Based Classification of Emotional State Using an Autonomous Vehicle Simulator

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***Abstract*—Societal acceptance of self-driving cars (SDC) is predicated on a level of trust between humans and the autonomous vehicle. Although the performance of SDCs has improved dramatically, the question of mainstream acceptance and requisite trust is still open. We are exploring this question through integration of virtual reality SDC simulator and an electroencephalographic (EEG) recorder. In order for a passenger to build and maintain trust, the SDC will need to operate in a manner that elicits positive emotional response and avoids negative emotional response. In our experiment, a test subject was exposed to scenarios designed to induce positive and negative emotional responses, quantified by the EEG beta wave to alpha wave power ratio. As predicted, an increase in the beta to alpha power ratio was observed when the test subject was exposed to stress inducing situations inside the SDC simulator. Our results are expected to inform the design and operation of an EEG-based supervisory feedback control module or artificial intelligence (AI) that monitors the emotional state of passengers and adjusts the AI control parameters accordingly.**

***Index Terms*—Electroencephalogram (EEG), Autonomous System, Self-Driving Car**

I. Introduction

Google, Tesla, Mercedes-Benz, Ford, and others have created semi-autonomous cars, and they predict mass production of fully self-driving cars (SDCs) in the early 2020s [1]. Widespread adoption of SDCs is dependent on consumers experiencing and maintaining positive emotional responses in SDCs. Electroencephalography (EEG) provides a non-invasive way to monitor brainwave activity, and a large body of research has focused on relating EEG responses to emotional states [2]–[4]. Recently, due to advances in dry electrode techniques and machine learning algorithms, there has been a proliferation of consumer grade and real-world applications of EEG for brain computer interfaces (BCI) [5]. EEGs are an appropriate choice to monitor SDC passenger response as they offer excellent temporal resolution [6].

In the experimental study, we will evaluate real time SDC passenger emotional responses through EEG analysis of a passenger in a SDC simulator. The simulation is designed to elicit negative emotions in order to assess the level of passenger fear, stress and anxiety in response to autonomous control actions of the SDC. Ultimately, it is envisioned that such information can be used to develop and inform the SDC autonomous control of maneuvers that elicit negative emotional response in a passenger, and adjust its behavior accordingly.

Jun and Smitha [7] found that effective stress is indicated by a decrease of EEG alpha band power and increase in beta band power. Conventionally, the alpha band contains frequencies 8-12 Hz, and the beta band 12-30 Hz [8]. Haak et. al. [6] also found that there is a strong positive correlation between eye blinking frequency and the emotional stress level of drivers. Additionally, Putman at al. [9] found that slow wave (SW) / fast wave (FW) ratio weakly correlates with fear as well as anxiety. Ratios were calculated by dividing slow wave power density, i.e., theta 4-8 Hz and delta 0.5-4Hz, by fast wave power density, i.e., beta 12-30 Hz. Wang et al. [5] compared several spectral decomposition methods, and found that the power spectrum is the most robust feature in analyzing EEG waves for emotion features.

The uniqueness of this research lies in the immersiveness of the SDC simulator. Previous research does not appear to have implemented a virtual reality (VR) headset along with a motion chair to create a SDC simulation while monitoring the EEG response of the passenger. This work builds on our prior work from [10] that showed our simulator is highly effective for collecting real-time data from human subjects. The previous work required subjects to self report, while the implementation of an EEG will provide more objective data. Our primary goal is to classify participants emotional response while in positive and negative emotion inducing scenarios in the SDC simulator. The paper is organized as follows. Section II reviews relevant literature and work in the field. Section III describes the SDC simulator. Section IV covers the experimental procedure. Section V examines the EEG data acquisition, analysis and results. Concluding remarks are made in Section VI.

II. Literature Review

Regarding EEG applications to SDCs, Lin et. al. [11] found that the EEG responses of the alpha and gamma bands in the left and right motor cortex, parietal, lateral occipital, and occipital midline brain areas were highly correlated to subjective motion sickness levels. They created a driving simulator and implemented a neural fuzzy inference network to estimate a car passenger's sickness level based on EEG features while in the simulation. The overall performance of this model achieved a prediction accuracy of 82%.

Yeo et. al. [12] created a support vector machine (SVM) EEG classifier that could correctly identify if a driver was in drowsy state with 99.3% accuracy and was able to predict when drivers enter a drowsy state with a 90% accuracy. Dominant beta wave activity indicated that a driver was alert, while a decrease in the amplitude or frequency of the alpha rhythm indicated a drowsy state. Fast eye blinks were associated with alertness and slow eye blinks were associated with a drowsy state. The extracted features came from the power spectrum of each 10 second EEG epoch.

EEG can be applied as a form of systems control. Meng et. al. [13] found that subjects who wore a noninvasive EEG could modulate their brain activity to control a robotic arm in order to perform reach and grab tasks in three dimensional space with a high level of accuracy. Control in three dimensions was achieved by a two-step sequential experimental design with control of the robotic arm reduced in each step to a two dimensional plane. Brain wave activity was monitored in the motor cortex and participant imagination of movement in the left hand, right hand, both hand, and relaxation corresponded to the respective left, right, up, and down movement of the robotic arm.

Göhring et. al. [14] created a car controlled by the user's modulation of brain waves while wearing an EEG. In one protocol, the car is completely controlled by the user's brain waves, but the precision of the vehicle control was not high enough to be used in real world scenarios. In the other protocol, the user is prompted to make choices (i.e., left or right turn) at certain decision points in the course. These results found a high level of precision.

III. Simulation Setup

The SDC virtual reality simulator is based on fusion of an Oculus Rift headset with an Atomic A3 Full Motion Simulator. Figure 1 shows a participant in the simulator.

Fig. 1. Participant using the SDC simulator.

Driving situations were recorded using the GoPro Fusion Camera and edited using the GoPro Fusion Studio to produce 360 degree video. The videos were exported from Fusion Studio at 4k resolution as MP4s along with 360 degree MP3 audio files. The Oculus Rift head set outputs 1080x1200 resolution per eye, at a 90 Hz refresh rate, a 110 degree field of view, and has headphones which output a 3D audio effect [15]. While wearing the Oculus Rift VR headset, the participant can freely move their head 360 degrees to see the complete scene. See figure 2 for the participants view inside the simulator.

Fig. 2. View from the simulation. Each frame represents the participant's view as they turn their head to look around, illustrating the 360 degree view inside the simulator.

The Atomic A3 Full Motion Simulator can move up to 71 degrees per second across a full 27 degree dual-axis movement range [16]. The combination of complete visual, audio, and movement immersion provides a convincingly realistic simulation. The Atomic A3 Simulator receives telemetry data that has pitch values for front and back movements and roll values for left and right movements. The Atomic A3 telemetry data was generated and played using Simphinity Motion Software. The application is executed on an AlienWare Area-51 Desktop equipped with an Intel Core i7-5960X processor along with dual NVIDIA GeForce GTX Titan Z graphics cards.

IV. Experimental Procedure

A. Experiment Design

In this phase of the research, only one test subject was exposed to the simulation. The test subject was exposed to two different simulation scenarios. The subjects brain waves were monitored during both simulation scenarios that lasted approximately 2 minutes each. In the first scenario (Scenario 1), the SDC performed smooth highway driving. The SDC maintained a comfortable amount of distance from other vehicles and followed all rules of the road. In the second scenario (Scenario 2), the SDC drove erratically around a residential neighborhood violating common rules of the road. The SDC ran through a stop sign and nearly collided with another vehicle. It was predicted that the EEG data would indicate a positive emotional state in Scenario 1 and a negative emotional state in Scenario 2.

V. EEG based emotional classification

Figure 3 illustrates the pipeline used to classify emotional state from the EEG data that we collected. MATLAB was used for all data analysis.

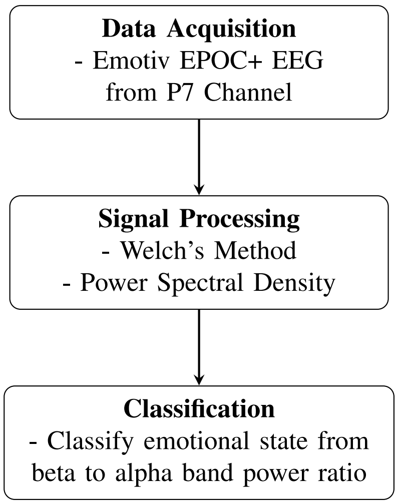

Fig. 3. Workflow of EEG data analysis

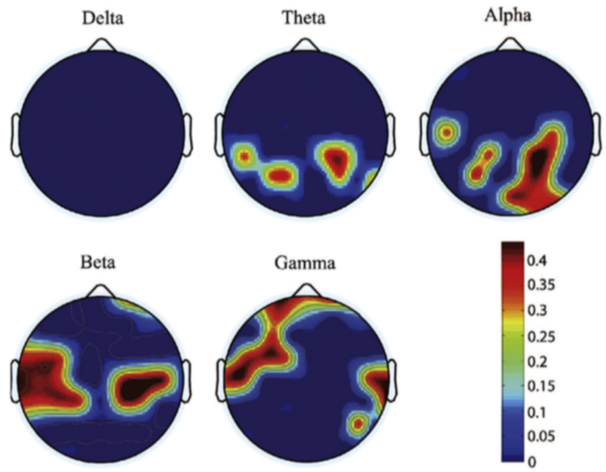

Fig. 5. Distribution of the top 50 subject-independent features for emotional state from Wang et. al. [5].

A. Data Acquisition

The Emotiv EPOC+ was used for EEG signal acquisition. The EPOC+ records signals from 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4). Two electrodes are used as references (CMS/DRL), the P3/P4 locations [17]. The 10-20 methodology of electrode application was used [18]. See Figure 4 for electrode placement. The signal was sampled at 128 Hz [17].

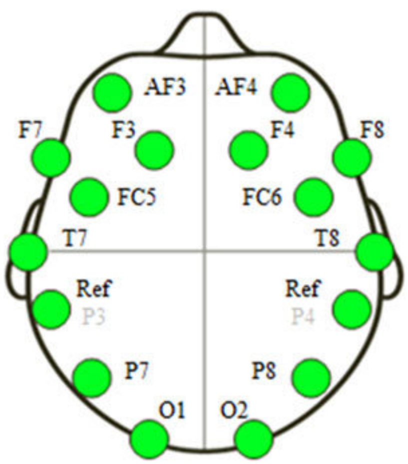

Fig. 4. Emotiv EPOC+ EEG electrode placement [19].

Based on the previously discussed research [5], [7], [9] the ratio of the average power between the beta and alpha waves was used as the main feature to determine emotional state. A high beta/alpha power ratio indicates negative emotional response. A low beta/alpha ratio indicates positive emotional response. The average power in the delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), and beta (12-30 Hz) is computed from the PSD.

Wang et. al. [5] found that the features with the most information on emotional response were mainly on right occipital lobe and parietal lobe in alpha band, the parietal lobe and temporal lobe in beta band, left frontal lobe and right temporal lobe in gamma band, as shown in Figure 5. It seems reasonable that these emotional response brainwaves do not appear to originate in the frontal cortex associated with higher thought processes and planning, but are closer to the occipital, brain stem, and limbic system where emotions are thought to be processed. The P7 electrode was the channel used for the signal processing and data analysis. In future phases of the research, more channels and interaction between channels will be analyzed.

B. Signal Processing

Beta to alpha EEG band Power Spectral Density was estimated using Welch's method with 50% windowing overlap, i.e., 128 Hz sampling rate over consecutive 4 second blocks. The ratio was calculated using the average power bands.

C. Results

As predicted, a higher average beta to alpha power ratio was observed in Scenario 2 then in Scenario 1. The average beta to alpha power ratio in Scenario 1 was -4.05 dB, and the average beta to alpha power ratio in Scenario 2 was -1.93 dB. The results can be seen in Figure 6. Spikes in the beta to alpha power ratio in Figure 6 can be related to specific events in the SDC simulation. In Scenario 2, the spike at the 11 second mark occurs when the SDC simulation runs a stop sign and nearly collides with another car. The spike at the 50 second mark in Scenario 2 occurs when the SDC aggressively drives around a winding road in a residential neighborhood, and the spike at 90 seconds occurs when the SDC abruptly stops at an intersection.

VI. Conclusion

This works indicates the effectiveness of using the beta to alpha power ratio as an indicator of emotional state while a participant is in the SDC simulator. In our future work, we will implement templates from our sequential and structured

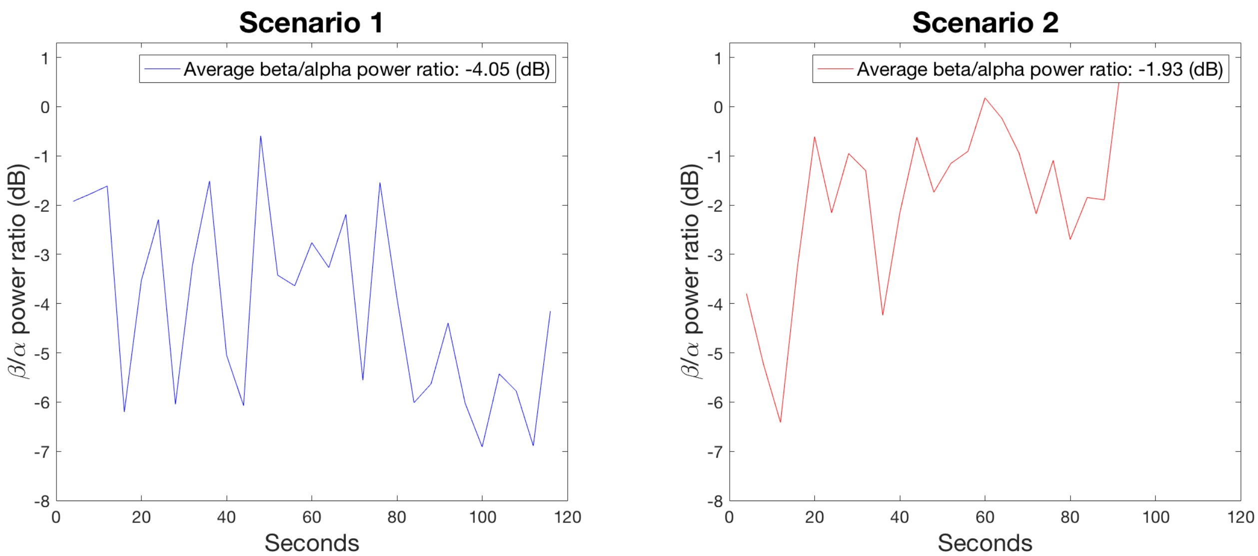

Fig. 6. Time series displaying the beta to alpha power ratio in Scenario 1 vs. Scenario 2.

trust assessment model from [20], and will evaluate a larger number of test subjects in the simulator.

EEG data has a low signal to noise ratio, therefore, it can often be difficult and time consuming to manually classify a data set, making a machine learning based classifier necessary for large sets of data. Prior research has shown that Linear SVM and MLP neural networks are good options to classify EEG data [21]. Future work will implement a machine learning classifier to determine the subjects emotional state. The ultimate goal is to lay the foundation to create a resilient supervisory feedback control module that monitors passengers state and acts as a feedback loop to modulate the control actions of the SDC.

VII. Acknowledgments

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