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Alterations in Multi-channel EEG Dynamics During a Stressful Shooting Task in Virtual Reality Systems

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***Abstract*— This paper explores power spectrum-based features extracted from the 64-channel electroencephalogram (EEG) signals to analyze brain activity alterations during a virtual reality (VR)-based stressful shooting task, with low and high difficulty levels, from an initial resting baseline. This paper also investigates the variations in EEG across several experimental sessions performed over multiple days. Results indicate that patterns of changes in different power bands of the EEG are consistent with high mental stress levels during the shooting task compared to baseline. Although there is one inconsistency, overall, the brain patterns indicate higher stress levels during high difficulty tasks than low difficulty tasks and in the first session compared to the last session.**

I. Introduction

Recent reports from American Psychology Association projects that an estimated 8 in 10 adults experience stress in their daily lives [1]. As per the circumplex model of affect, where emotions are represented in two dimensions - valence and arousal, stress is the state of negative valence and high arousal and lies in upper-left quadrant of the emotional space [2]. Apart from having a detrimental effect on one's physical health and perceptual-motor skills, stress negatively affects higher-order cognitive processes like attention, memory, decision making, resulting in impaired cognitive function and reduced performance [3]. As per the Yerkes-Dodson principle, relationship between arousal and performance has an inverted-U curve, where high levels of arousal result in negative stress and reduced performance [3]. Hence, early detection of stress would improve one's health and quality of life and improve performance-based tasks.

VR-based human training systems incorporate affective computing principles and technologies to customize the training aids as per the user's emotional or cognitive states as indicated by their physiological responses, resulting in improved training outcomes [4]. One such VR-based training system for shooting marksmanship [5] is used in this study to elicit physiological stress responses at multiple levels by changing the difficulty levels of the shooting task.

Although the response to stressors can be physiological, behavioral, or psychological, stress mechanism originates in the brain wherein, after some initial processing, it is relayed to other parts of the body via activation of the Hypothalamus Pituitary Adrenal axis and Sympathetic Adrenal Medullary pathways [6]. Hence, EEG signals have been used to assess stress during stressful neurophysiological activities [7], [8].

This paper investigates systematic and consistent patterns in 64 channel EEG signals during the VR-based stressful shooting task [5] and identifies changes in brain activity from an initial resting baseline (BL). It also analyzes the variations in the EEG signals across experimental sessions performed over multiple days. Power spectrum-based EEG features have been used in this study to evaluate three key hypotheses: (1) stress level increases during the shooting task as compared to the resting baseline (BL), (2) stress level is higher in a high difficulty (HD) shooting task as compared to a low difficulty (LD) shooting task, and (3) stress level reduces as the participants go through multiple sessions. The remaining paper is organized as follows: Section II describes the methodology for data acquisition, signal pre-processing, and feature extraction. Experimental results are discussed in Section III, and Section IV concludes the paper.

II. Methodology

A. Experimental Setup and Data Acquisition Protocol

Data for this study was collected from participants (n = 31, 18 males, 13 females, age: 24.99 ± 3.21 years) recruited from the student population at the University of Maryland, Baltimore County. Each participant signed an Informed Consent approved by the Institutional Review Board. There was no specific exclusion criteria for this study to retain the real-world variability inherent to actual VR-based training. More details on the VR system, Go/No-Go VR-based shooting task, data acquisition protocol, and the general procedures followed for the shooting sessions are described in [5].

Before the experimental sessions, the participants were familiarized with the VR system and performed practice trials. Then they participated in a thresholding session. Based on their performance in that session, individualized Target Exposure Time (TET) of the enemy and friendly soldiers were determined from a Gaussian distribution (range: 0.3s to 1.36s) for LD (mean: 0.86s) and HD tasks (mean: 0.56s). TET was set such that on average, 50% of enemy targets are hit in HD task, and 90% are hit in LD task.

Each participant performed in six experimental sessions where a session consisted of one LD task and one HD task interspersed with a brief period of rest and a one-minute resting BL. Each task consisted of 360 targets that popped up at random times, of which 90% were enemy and 10% were friendly. The participants had to shoot the enemy and spare the friendly ones. The order of LD and HD tasks was randomly counterbalanced across all participants and sessions. Each session had a one-minute initial BL and a one-minute final BL at the end of the session. During these resting baselines, the participants were asked to remain quiet, still, and stare at a fixed dot at the screen's center.

B. EEG Signal Pre-processing

The EEG signal was obtained using a 64 channel (placed as per standard 10-10 electrode layout) EEG cap from the Biosemi ActiveTwo System (BATS) [9] at a sampling frequency of 2048 Hz per channel. EEGLAB Toolbox (ver. 14.1.2b) was used to pre-process the EEG signal and remove the artifacts [10]. The signal was re-referenced and down-sampled to 512 Hz, followed by high pass filtering with a cut-off frequency of 1 Hz. Large artifacts were removed using visual inspection for abnormal trends and extreme values, and bad channels were rejected based on channel statistics.

C. Feature Extraction

The continuous EEG signal was decomposed into frequency bands known to have distinct functional characteristics - Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Low Beta (12-16 Hz), High Beta (16-30 Hz), and Gamma (30-40 Hz). Power Spectral Density (PSD) was estimated by Welch's periodogram method (4s Hann window sliding with 50% overlap) in each band. The Absolute average Band Power (ABP) was computed from the area under the PSD curve in each band. The Relative average Band Power (RBP) was determined by expressing ABP as a fraction of the EEG signal's total power ($RBP = \frac{ABP}{TotalPower}$). Since all the brain lobes may not be equally affected during the task, all 64 channels have been included in this analysis.

Four sets of features have been used to study the baseline-to-task variations. The first two sets consist of ABP and RBP computed for all six bands and 64 channels for the initial BL, LD task, and HD task in each participant's session. The other two sets are computed by scaling the ABP and RBP of the particular task by the ABP and RBP of the initial resting BL, respectively, and denoted by sABP ($= \frac{Task\_ABP}{BL\_ABP}$) and sRBP ($= \frac{Task\_RBP}{BL\_RBP}$). The mean value of each feature was also computed for each task at each channel by removing 4% of outliers at both the tail ends of the distribution and averaging it over all sessions of all participants, and finally, converting it into units of dB to achieve normal distribution for statistical analysis. A paired sample t-test was done between LD and HD tasks using ABP, RBP, sABP, and sRBP, and p-values were computed in each case for the null hypothesis. After artifact correction, a total of 160 sessions across 30 participants were used for this analysis.

The session-to-session variation was analyzed between HD tasks of Session 1 (first) and Session 6 (last) using these four sets of features. For a particular session, the mean value of each feature was computed for the HD task at each channel after 4% outlier rejection as above. A paired sample t-test was done between the two sessions, and p-values were computed. A total of 19 participants for whom clean data was available for both sessions were used for this analysis.

III. Experimental Results & Discussion

Fig. 1 shows the mean RBP and mean ABP in each band for BL, LD task, and HD task after averaging across all channels, sessions and participants. ABP is lower for BL than LD and HD tasks, except for Alpha band. On the contrary, RBP is higher for BL than LD and HD tasks except for Delta band, where it is lower. Both ABP and RBP have similar values for LD and HD tasks in each band.

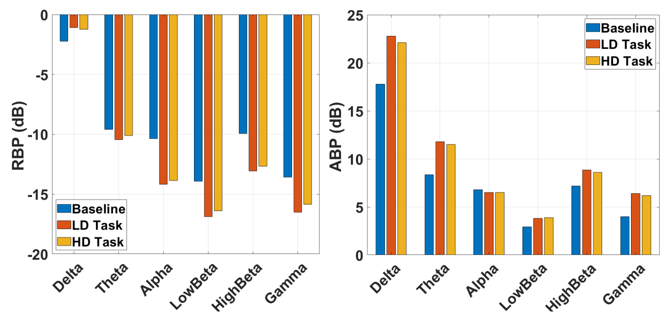

Fig. 1. Bar Plot of average RBP and average ABP across all channels, sessions and participants in each frequency band for BL, LD, and HD tasks.

A. Baseline to Task Variation

Fig. 2 and Fig. 3 show the distribution of means, of sABP and sRBP in dB, for HD task in different brain regions for various bands, respectively. Positive values indicate an increase in power, and negative values imply a decrease during the task compared to BL. As shown in Fig. 2, ABP increases at all channels during HD task across all bands, with the lowest increase observed for the Alpha band. The Highest increase for all bands happens in pre-frontal, lateral-frontal, and temporal areas. The lowest increase occurs in the central pre-motor and motor cortex area along the midline and the parieto-occipital area for all bands.

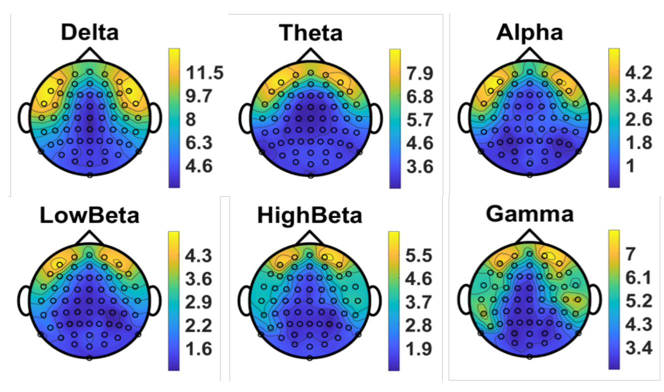

Fig. 2. Distribution of the mean of sABP (dB) for HD Task.

As shown in Fig. 3, Delta RBP also increases across all the electrode positions. The maximum increase is observed in the temporal lobe, lateral pre-motor, and motor cortex areas. The lowest increase is observed in the occipital, parietal, and central regions along the midline. An increase in Delta power in the frontal lobe has been observed during mental tasks, which involve attention to internal processing and simultaneous inhibition of distractors or no-go stimuli, affecting the task's performance [11].

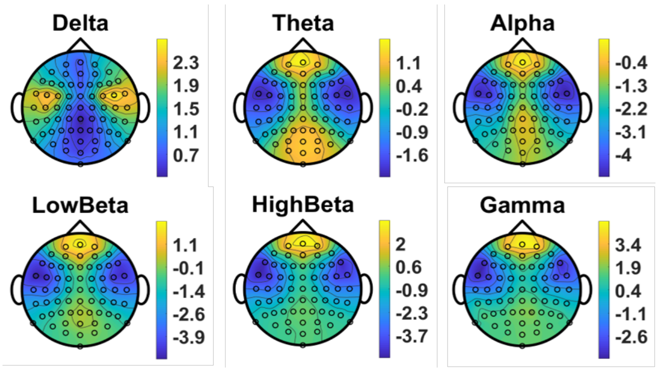

Fig. 3. Distribution of the mean of sRBP (dB) for HD Task.

Fig. 3 also indicates that Theta RBP and Gamma RBP increased in the pre-frontal area, occipital lobe, and along the midline in central and parietal regions. Increased pre-frontal Gamma RBP has been observed during mental arithmetic tasks combined with negative social feedback [12] and could indicate higher mental stress. Theta power has also been observed to increase in response to higher task demands, and error-related processing [13].

In Fig. 3, RBP in the Alpha band decreased across all electrode positions, with the lowest decrease observed along the midline in the frontal, central, parietal and occipital lobes. RBP for the Low Beta band and High Beta band increased in the pre-frontal area and decreased in other regions. Alpha power, especially in the frontal lobe, is negatively correlated with stress. It increases during physically and mentally relaxed conditions [7] and is inhibited during active attention tasks [14]. Beta power in the frontal lobe is positively correlated with stress and increases with higher demands on attention, cognitive load, and performance [15]. Hence, decreased Alpha RBP and increased Beta RBP in pre-frontal areas could indicate higher mental stress during HD tasks.

The Alpha Frontal Asymmetry Index (AI), associated with the valence dimension, has been a popular feature in stress studies [7]. In stressed scenarios, the left pre-frontal cortex, associated with positive valence states, has been shown to have lower power compared to the right hemisphere, which has been associated with negative avoidance type emotions [16]. In this case, there is no asymmetry observed in the Alpha band for both LD and HD tasks.

B. LD Task to HD Task Variation

Paired sample t-test was performed using the four sets of features (in dB) to locate channels with significant differences ($p-value < 0.05$) between HD and LD tasks. Fig. 4 and Fig. 5 show the distribution of the difference between mean ABP and mean RBP of HD and LD tasks, respectively and indicate whether the power at channels with significant differences has enhanced or reduced. Scaled counterparts, sABP, and sRBP show similar trends for all bands.

In Fig. 4, a significant decrease in Delta ABP was observed in the pre-frontal area and occipital and parietal lobes during the HD task compared to the LD task. On the contrary, Fig. 5 shows a significant increase in RBP during HD task for all other bands in those same areas.

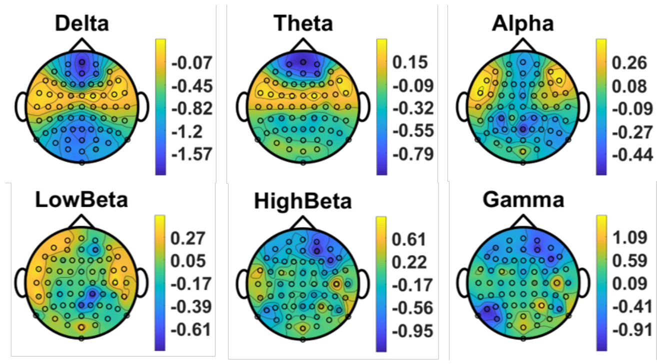

Fig. 4. Distribution of difference (dB) between mean ABP of HD and LD task. Significant decrease ($p-value < 0.05$) is only in Delta band in pre-frontal area and in occipital and parietal lobes.

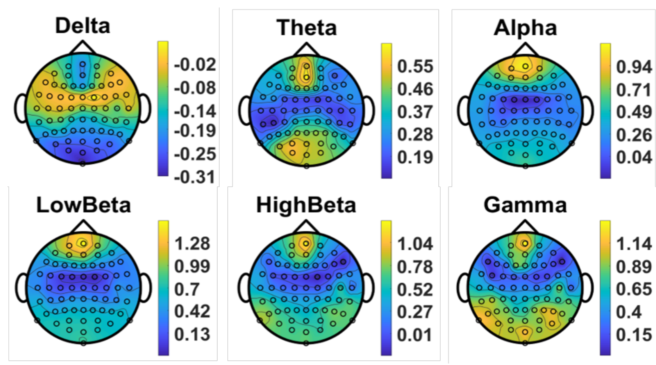

Fig. 5. Distribution of difference (dB) between mean RBP of HD and LD task. Significant difference ($p-value < 0.05$) is in pre-frontal area and in occipital and parietal lobes, for all bands except Delta band. Theta RBP increases significantly at some frontal channels as well.

In Fig. 5, increased pre-frontal Gamma RBP could indicate higher stress in HD tasks than LD tasks. Increased Theta RBP in pre-frontal areas could also imply higher task demands and error-related processing in HD tasks than LD tasks. Increased Beta RBP in the pre-frontal and frontal lobe could be due to higher stress and higher demands on attention and cognitive load during HD tasks. The increased parietal and occipital lobe activity in all bands during HD tasks could indicate increased temporal attention demands to shorter target exposures in HD vs. LD tasks. The marginal reduction in Delta RBP during HD task could be due to greater relative inhibitory control demands under time stress in HD vs. LD task [11]. The increased Alpha RBP in the pre-frontal and frontal lobe in HD vs. LD contradicts expectations as Alpha typically decreases with stress and cognitive demands [14] and would need further analysis.

C. Session to Session Variation

HD task was used to analyze the changes in brain activity between Session 1 (first) and Session 6 (last), and a paired sample t-test was performed to compare the two sessions. Fig. 6 and Fig. 7 show the difference (in dB) between mean ABP and mean RBP for Session 1 and Session 6 ($Session1 - Session6$), respectively and indicate whether the power at significant channels has increased or decreased.

Fig. 7 shows that RBP was significantly reduced in Delta band in the occipital lobe in Session 1 vs. Session 6. RBP was enhanced considerably in all other bands in the occipital and parietal lobes and pre-frontal and anterio-frontal areas in Session 1. The trends of change from Session 1 to Session 6 are comparable to the trends of change from HD task to LD task, described in the previous subsection, in all the bands. The performance statistics show an increase in average shooting success rate from 50% to 60% for HD tasks which suggest learning or practice-related adaptations in the above spectral changes [13].

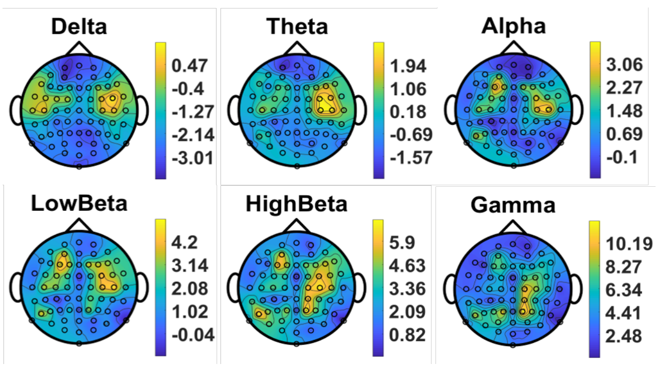

Fig. 6. Distribution of difference (dB) between mean ABP of HD Task of Session 1 and Session 6. Significant differences ($p-value < 0.05$) are only in pre-frontal area and parietal lobe in Delta band.

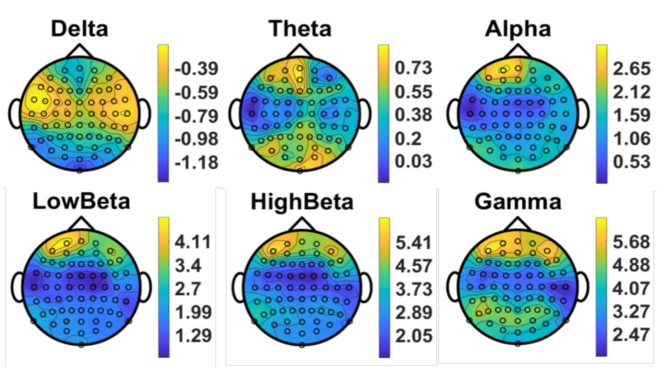

Fig. 7. Distribution of difference (dB) between mean RBP of HD Task of Session 1 and Session 6. Significant differences ($p - value < 0.05$) are observed in occipital lobe for Delta band and in occipital lobe, parietal lobe, pre-frontal and anterio-frontal areas for other bands. No significant channels were observed in Theta band.

IV. Conclusion

Overall, RBP appears to differentiate brain state changes better than ABP, between task difficulty conditions and changes over time with practice. The reasons for that would need to be further investigated. The pattern of changes in different EEG bands is consistent with higher mental stress levels in LD and HD tasks compared to BL. But, upon comparing changes in EEG signals across time (Session 1 vs. Session 6) and difficulty levels (HD vs. LD), interesting results were observed in Alpha band that do not appear to suggest the changes are associated with changes in stress level. However, increase in pre-frontal Gamma RBP and Low Beta and High Beta RBP in Session 1 and during HD tasks indicates increased mental stress in both cases compared with their counterparts. Due to paucity of time, the ocular artifacts could not be removed. These might have contributed to some of the observations, and will be addressed in future extension of the work.

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