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A SMALL STEP TOWARDS THE DETECTION OF MENTAL FATIGUE INDUCED BY BCI-HMD TRAINING

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ABSTRACT: We used a proprietary constructed brain-computer interface system with a head-mounted display for motor neurorehabilitation training of a subject after a stroke. This study analyzes quantitative EEG (qEEG) changes during resting state periods before and after the neurorehabilitation training. Eyes closed and eyes open resting state EEG collected during 13 training sessions is analyzed to determine qEEG changes indicating mental state changes like increased mental fatigue, tiredness, or sleepiness. We decomposed the EEG spectrum into oscillatory and fractal parts, allowing us to investigate changes in the oscillatory component of qEEG separately. We observed increased post-training oscillatory EEG amplitudes in slow frequency bands (delta and theta) and decreased in faster alpha to beta bands. A shift to a slower frequency of the dominant alpha frequency was also observed in the post-training resting state EEG. Compared with existing literature, these changes indicate increased mental fatigue and sleepiness.

INTRODUCTION

A growing body of evidence suggests that integrated technologies of brain-computer interfaces (BCI) and virtual reality (VR) environments provide a flexible platform for neurorehabilitation therapies, including significant post-stroke motor recovery and cognitive-behavioral therapy. If VR scenarios are realized through head-mounted displays (HMDs), a compact BCI-HMD system that is exceptionally flexible and rich for implementing various scenarios and tasks can be constructed. As some studies have shown, BCI-based neurorehabilitation therapies are effective in improving the motor abilities of stroke survivors [2, 3].

One of the challenges of BCI is its decreased performance over time, making it unreliable for long-term use [4]. The oscillations of psychological states can cause such inconsistencies. While performing BCI tasks, mental states such as level of frustration, mental fatigue, and attention may shift, therefore influencing the outcomes of a BCI session [5]. This is a concern because stroke survivors exhibit a higher prevalence of fatigue; it is often severe and frequent even long after stroke [6]. Therefore, it is important to consider mental states, especially fatigue, for stroke patients while performing rehabilitation procedures. Previous studies concentrated on subjective fatigue measurements, such as the Visual Analogue Scale (VAS) or other qualitative reports; however, EEG has been the more reliable predictor due to its temporal precision [2, 7, 8].

Fatigue is a decreased ability to initiate or sustain voluntary actions, including difficulties with alertness, mental performance, and reduced efficiency. It is gradual and cumulative and applies to psychological and physical activity. Mental fatigue is concerned explicitly with reduced or impaired cognitive functions that are believed to be caused by prolonged cognitive activity. Mental fatigue can also influence physical performance.

There have been different approaches to defining mental fatigue with EEG, including detecting an increase in the ratio of slow wave to fast wave as the fatigue progresses [9]. Additionally, particular areas of the brain and frequencies that indicate the increase in fatigue have been determined. Some of the findings seem to contradict each other. For example, a study by Eoh and colleagues (2005), and a study by Stern found a decrease in the alpha band as drowsiness increased [11, 12]. However, a later study by Jap and colleagues found that alpha waves increased in the occipital lobe as fatigue progressed [13]. On the other hand, Eoh and Jap outlined that the beta band decreases with the progression of fatigue in temporal and frontal areas, and the (theta+alpha)/beta ratio increases [11, 13]. Both studies looked more into the drivers' fatigue and sleepiness, possibly influencing the outcomes. Trejo and colleagues (2015) came to the same conclusions as Jap and colleagues, stating that an increase in parietal alpha and frontal theta was present, along with a shift in alpha frequency to the lower alpha band [13, 14]. According to the meta-study, the increase of theta waves in the frontal, central, and posterior regions is associated with fatigue, additionally, the rise of alpha in central and posterior frequency serves as a biomarker of fatigue [15].

Other researchers have previously investigated fatigue in BCI rehabilitation. In 2010, a paper was published by Prasad and colleagues who researched BCI used for upper-limb recovery [2]. The Visual Analogue Scale

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(VAS) was used to examine fatigue. Some participants exhibited increased mental fatigue, but the details were unclear as it did not allow for temporally precise results. The study by Foong and colleagues (2020) also concentrated on the neurorehabilitation of upper limbs for stroke survivors through the use of BCI technologies [16]. To examine mental fatigue, the researchers extracted 3-second data before each trial to correlate it with the subject's performance, and they concentrated on the shifts of amplitude of beta waves across different brain areas separately (frontal, central, parietal-occipital). The findings showed a significant positive correlation of beta power with accuracy in frontal and central brain regions, which suggested that mental fatigue in BCI tasks was associated with the performance outcomes [16]. However, the shortcoming of this approach is that it only considers beta bands without looking into theta, delta, and alpha, which were associated with mental fatigue in the previous literature. On the contrary, a study by Talukdar and colleagues found that there is a significant increase of spectral power in the range of 0.1-12 Hz but no significant findings in the beta band after performing the MI task on BCI [17]. With that in mind and to our knowledge, no studies have examined the effects of BCI-HMD systems on mental fatigue after performing MI tasks.

In this study, we used a proprietary constructed real-time BCI-HMD system for motor rehabilitation of the upper limbs of subjects after stroke [18]. We performed a series of 13 training sessions (days) on a subject with post-stroke motor impairment of the left upper limb. Part of the training process is the collection of EEG data during resting state periods preceding and following the training itself. This paper focuses on quantitative EEG analysis (qEEG) of changes the training can induce on the resting state eyes closed (EC) and eyes open (EO) EEG, or passive BCI. We focused on the oscillatory part of the EEG spectrum in the frequency range from 2.5 Hz to 18.0 Hz. Significant post-training changes were observed in the EC condition, indicating EEG slowing. Changes in the EO condition were sporadic and restricted to faster alpha and beta EEG frequencies. A shift in the dominant alpha frequency to the lower alpha band was also observed. These changes align with changes associated with increased mental fatigue, as reported by Trejo and colleagues [14].

MATERIALS AND METHODS

In the study, the previously developed and described BCI-HMD system was used [18]. Its architecture is depicted in Fig. 1, representing the standard BCI design consisting of

- signal acquisition,
- signal processing and classification and
- environment control.

Publicly available OpenVibe[1] software for BCI and real-time neuroscience interconnect three major blocks of the

[1] http://openvibe.inria.fr

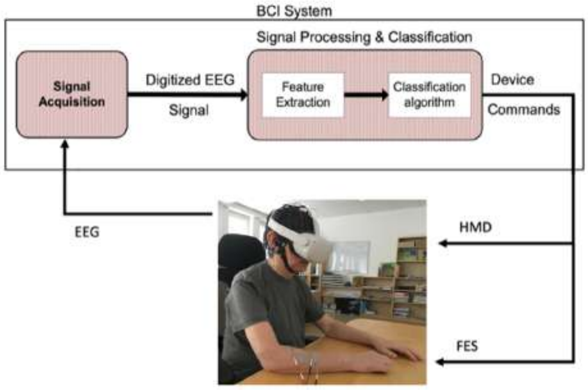

Figure 1: The architecture of the brain-computer interface with a head-mounted display (BCI-HMD) and the functional electrical stimulation (FES) element.

BCI-HDM architecture. An autonomous Oculus Quest 2 (Meta Platforms, Inc.) headset with a fast processor, a new-generation graphics card, and 256 GB of internal storage is used as the HMD. The neurorehabilitation system is also enriched with the functional electrical stimulation (FES) component applied to selected muscles. This is done through the programable two-channel externally controlled Microstim FES device (Medel GmbH).

The main element of BCI training is the task of motor imagery (MI), during which the subject imagines the movement without including movement of the limb. During this effort, required changes in brain activity are recorded using an EEG on the subject's scalp. If these changes are detected successfully, the requested visualization in the VR environment will begin. Such a visualization could exhibit an avatar's hand grasping a cup on the table (Fig. 2). In this study, we used three randomly varying tasks: grasping a cup, a cube, and turning a key in a lock. Because our goal is not the description and analysis of the BCI training itself but the analysis of brain activity changes during the resting state before and after the training, we do not describe the design of the BCI-HMD further and refer the reader to [18].

Figure 2: An example of a virtual environment (a cup) with an object grip animation.

Experimental Protocol: Each training day (session) started with two minutes of the resting state block with eyes closed (EC) followed by two minutes of the resting state block with eyes open (EO). The same EC and EO resting state EEG was recorded after each BCI-HMD training session. During the EO condition, the subject fixated his eyes on a small cross on the wall in front of him.

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A self-made questionnaire was provided at the beginning of each session and after completing resting state EC and EO EEG recordings. The subject was asked to answer the question *"Do you feel tired?"* on a seven-level scale (1 - absent feeling, 7 - extreme feeling). In addition, after each block of BCI-HMD training trials, six questions focused on the subjective evaluation of cybersickness and tiredness were applied. However, in this paper, EEG data recorded during the BCI-HMD training and their connection to subjective assessment of cybersickness and mental fatigue development during the training itself are not analyzed.

The BCI-MHD experiment consists of a series of trials in which the subject is instructed to imagine a movement of their avatar hand in VR mentally. In this study, each session consisted of three blocks with ten MI trials in each block.

Participant: The subject of this study is an 86-year-old male who has experienced left-sided hemiparesis due to a stroke in the basal ganglia region on the right side with residual upper limb weakness (acral part). After the stroke, he also suffers from fatigue syndrome with Parkinson's syndrome. In the time before the stroke, the subject was a healthy, active athlete with no presenting psychiatric diagnosis.

The subject participated in 13 days of BCI training from May 11, 2023, to June 22, 2023. The sessions occurred at intervals of 1 to 6 days.

EEG Signal Acquisition and Processing: Wireless g.Nautilus PRO FLEXIBLE FDA-cleared and CE-certified recording system was used for EEG data acquisition. The current experiment included 11 Ag/AgCl wet electrodes attached to a fabric cap following a 10-20 international system. The electrodes included on the right hemisphere were FC4, C2, C4, C6, and CP4; the electrodes on the left hemisphere included FC3, C1, C3, C5, CP3, O1, as well as a linked-ears reference and one ground electrode AFz.

For resting state conditions (EC/EO), we performed an initial analysis with the sampling rate set to 250 Hz. EEG data processing consisted of multiple steps applied in Brain Vision Analyzer 2.3.0[2] (BVA) with templates and expert supervision. First automatic artifact detection step with criteria of maximal allowed voltage set at 50 μV/ms, maximal absolute amplitude set at 70 μV, lowest allowed activity in intervals of 100 ms set to 0.5 μV, and maximally allowed difference of voltages in intervals of 20 ms was to 70 μV was applied. EEG traces with detected artifact segments were then visually inspected by a trained expert, and artifact markers were edited.

Artifact markers were exported from the BVA software, and further analysis was carried out in the MATLAB[3] software.

EEG band amplitudes were analyzed for the oscillatory part of the frequency spectrum. The decomposition of the total frequency spectrum into fractal (representing background EEG) and oscillatory components was done using the irregular-resampling auto-spectral analysis (IRASA) [19]. IRASA decomposes the amplitude spectrum of each segment into a fractal (scale-free) and an oscillatory part. Different mechanisms may generate EEG oscillatory and fractal components, so it is essential to estimate them separately, mainly when the measurement focuses on localized narrow-band oscillatory rhythms, as is the case here. The oscillatory part of the amplitude spectrum was obtained by subtracting the fractal part from the total spectrum estimate. Negative values of the oscillatory spectrum were set to zero. In the study, we focused on the oscillatory part of the spectrum to measure band amplitudes from 2.5 Hz to 18.0 Hz. Both spectrum parts were computed with a resolution of 0.4883 Hz. The analyzed EEG endpoints were standardized quantitative qEEG measures in the following ranges: delta (2.5-4Hz), theta (4-8 Hz), alpha1 (8-10 Hz), alpha2 (10-12 Hz), beta1 (12-15 Hz), beta2 (15-18 Hz), alpha individual (6.4-9.8Hz). Additionally, ASI (alpha slow wave index defined as a ratio of (alpha1 + alpha2)/(delta + theta)), TBR (theta/(beta1 + beta2) ratio), and BAR (beta1/(alpha1 + alpha2) ratio) derived measures were included.

Using a paired t-test, we analyzed differences between the above-defined measures computed from EEG traces recorded before and after the training. This testing was done separately for each electrode in eyes closed and eyes open condition.

In the subjective evaluation of fatigue, the days were separated by the answers to the tiredness question. The first group included sessions in which increased tiredness was reported after the BCI training compared to the pre-training response (sessions 1, 2, 8, 11, and 12). The remaining eight sessions created the second group, including the days of the same reported fatigue or decreased fatigue after the training session. Then, the percent of change (PC)

$$PC = (post - pre)/(post + pre)$$

between post- and pre-training endpoint values were computed for each endpoint and electrode. The PC of each of the two groups was computed by averaging all sessions corresponding to that group.

RESULTS

Eyes Closed: Fig. 3 shows a summary of significant before and after BCI-HMD training amplitude band differences. A significant after-training delta increase can be observed at the C2 and CP4 electrodes. Theta significantly increased at both fronto-central FC3 and FC4 EEG channels. Alpha1 post-training decreased at the O1 and CP4 electrodes. Alpha2 post-training decreased at the C1, C2, and FC4 EEG electrodes, but increased at the O1 electrode. Significant changes in the beta range were sporadic and limited to the beta1 post-training increase at O1.

[2] https://www.brainproducts.com/solutions/analyzer
[3] https://www.mathworks.com

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The derived ASI, TBR, and BAR measures mimicked the observed changes in amplitude bands and indicated overall EEG slowing. Increasing slower delta and theta frequency bands and decreased alpha bands are reflected by a significantly broader post-training ASI decrease in the left hemisphere (FC3, C1, C3) and the right hemisphere (FC4, C2, C4, C6). TBR increases at the FC4 electrode and reflects an observed significant increase of theta at the same electrode site. A significant post-training increase in BAR was limited to the O1 electrode.

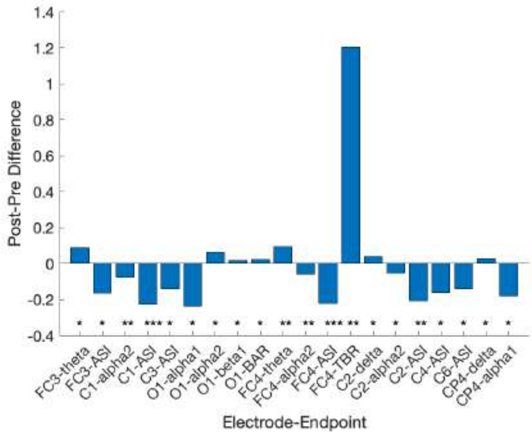

Figure 3: Bar chart showing significant post-training and pre-training amplitude band differences for the eyes closed (EC) condition. The statistical significance of the differences was tested using a paired t-test. Results are shown by EEG channel and amplitude band. Positive values indicate a post-training increase and negative values decrease. Values represent amplitude per Hz differences (µV/Hz). For ASI, TBR, and BAR, the values represent a ratio. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Fig. 4 shows oscillatory spectrum differences between post-training and pre-training spectrum averages calculated over 13 sessions. Pre-training and post-training oscillatory spectrum overlay is depicted in Fig. 5. As can be seen, the theta band significantly increased in frontal and central areas (more prevalent on the left side). There is also a decrease of alpha1 in central, frontal, and parietal electrodes, mainly on the right hemisphere.
When analyzing post- versus pre-training endpoint values grouped according to the subjective evaluation of tiredness, there was a 22.24% (at electrode C2) and 19.74% (at electrode CP4) PC increase in the delta band in the increased fatigue group. In the group where no increase in fatigue was subjectively indicated, the delta PC was 12.69% (electrode C2) and 7.43% (electrode CP4). Although limited to a single endpoint, these findings are consistent with some previous research [8, 20].

Eyes Open: Significant post-training changes in the EO condition were sporadic and restricted to faster EEG frequencies (alpha, beta) than the resting state EC condition. A summary of significant before and after BCI-HMD training amplitude band differences is shown in Fig. 6. A post-training increase was observed in alpha1 at CP4, but a more systematic decrease of alpha2 was

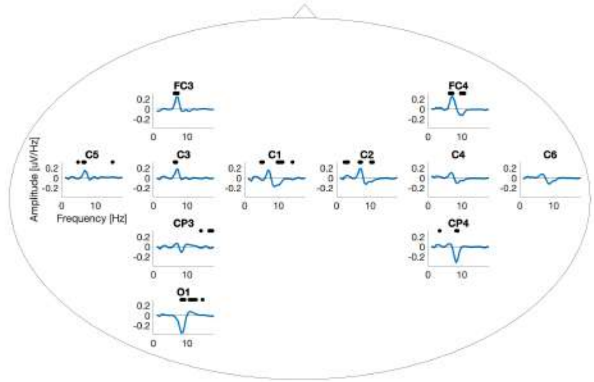

Figure 4: Eyes closed (EC) oscillatory spectrum difference computed as a difference between post-training and pre-training oscillatory spectrum averages calculated over 13 sessions. Positive values indicate a post-training increase and negative values decrease. Dots indicate frequencies where significant differences were observed using a paired t-test ($p < 0.05$).

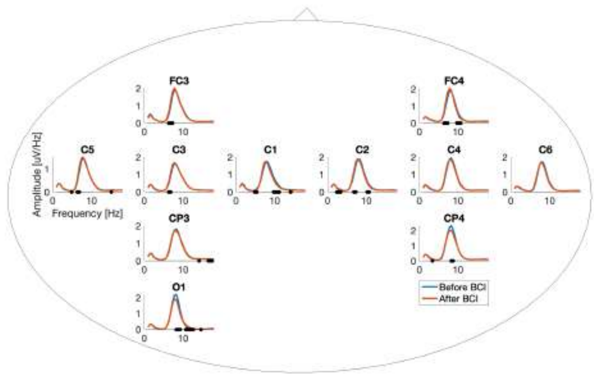

Figure 5: Eyes closed (EC) spectrum overlay of pre-training and post-training oscillatory spectrum averages calculated over 13 sessions. Dots indicate frequencies where significant differences were observed using a paired t-test ($p < 0.05$)

observed in the right hemisphere (C4, C6, CP4). TBR increased at CP3. This significant change in TBR is driven by post-training theta increase and beta decrease. The change can be observed in Fig. 7 and Fig. 8.
Similarly to Fig. 4, Fig. 7 shows significant EO changes depicted as oscillatory spectrum differences between post- and pre-training spectrum averages calculated over 13 separate sessions. Pre-training and post-training oscillatory spectrum overlay is depicted in Fig. 8. Around 9 to 10 Hz, a rapid negative to positive post-training change can be observed. This frequency span defines the subject's alpha frequency range, and the rapid change represents a shift from the dominant alpha to the lower alpha band.
No consistent results were found when subjectively reported fatigue levels collected before and after the training sorted endpoint values.

DISCUSSION

The study assessed mental fatigue using EEG collected

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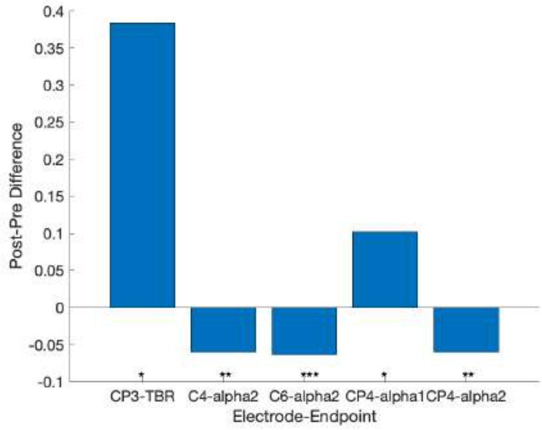

Figure 6: Bar chart showing significant post-training and pre-training amplitude band differences for the eyes open condition (EO). See Fig. 3 for description.

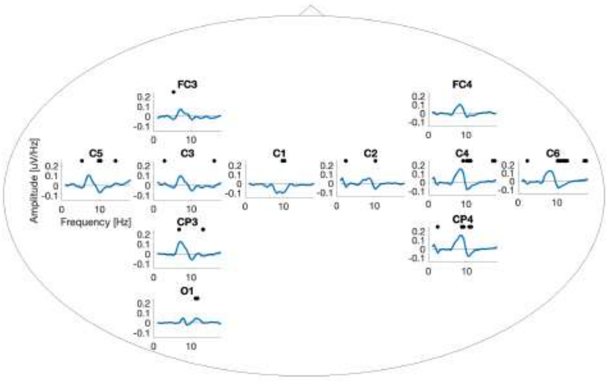

Figure 7: Eyes open (EO) oscillatory spectrum difference computed as a difference between post-training and pre-training oscillatory spectrum averages calculated over 13 sessions. Dots indicate frequencies where significant differences were observed using a paired t-test ($p < 0.05$).

from resting state EC and EO periods recorded before and after the BCI-HMD training. As previous research has shown, mental fatigue is associated with the increase of theta band power in the frontal area and alpha in the parietal area, as well as with a shift in alpha frequency to the lower alpha band [14]. These changes could be seen as a result of completing a monotonous task consisting of solving simple mathematical problems and lasting up to three hours. These findings were also restricted to the EO condition because subjects solved the task displayed on a screen [14]. In the current study, we observed a significant post-training theta band increase at the frontocentral spatial region, and this was true for the EC condition. This theta increase is also consistent with the findings by Jap, Barwick, and DeGennaro [7, 8, 13].

The alpha effect was less clear. Considering alpha1 and alpha2 frequency sub-bands, we observed an increased EO alpha1 in the right central-parietal region but a decrease of the same alpha1 in the EC condition. Alpha2 decreased in both EC and EO conditions, which was true mainly for the central and central-parietal regions, except

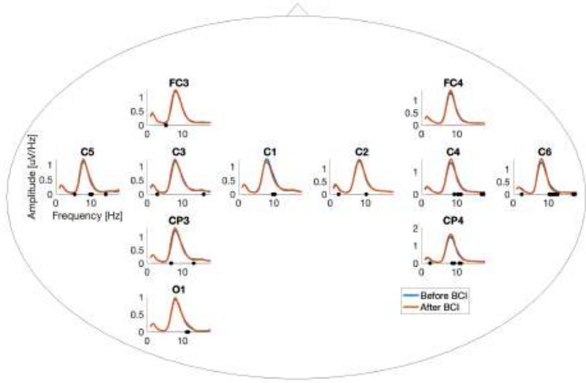

Figure 8: Eyes open (EO) spectrum overlay of pre-training and post-training oscillatory spectrum averages calculated over 13 sessions. Dots indicate frequencies where significant differences were observed using a paired t-test ($p < 0.05$).

for the O1 electrode in the EC condition, alpha2 post-training increased.

The described study analyzed only one participant; therefore, no more robust conclusions can be made from the findings, and broader research is necessary. Instead, the presented study serves as an introduction to the problem of induced mental fatigue in BCI-HMD MI training of stroke patients. The study doesn't address other essential elements that need to be controlled for, such as circadian rhythms, caffeine intake, the quality of sleep, and other phenomena affecting mental fatigue. Therefore, it remains an open question whether the reported post-training differences could be explained by mental fatigue or other possible factors associated with using the BCI-HMD system, such as visual fatigue, lack of motivation or interest, frustration, sleepiness, or even dizziness. The provided questionnaire considered some of those questions, and the obtained subjective scores will be analyzed in future research. Including these elements in further research may lead to a more precise separation of mental fatigue from sleepiness, lack of engagement, or other similar yet different mental phenomena.

CONCLUSION

The research findings could be utilized to compose customized machine-learning algorithms for motor rehabilitation of post-stroke patients using the BCI-HMD environment. Considering mental fatigue in training sessions could increase rehabilitation outcomes; more specifically, it could suggest improvements in task design and data analysis.

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