Adaptive Brain-Computer Interface with Attention Alterations in Patients with Amyotrophic Lateral Sclerosis

S. Aliakbaryhosseinabadi and N. Mrachacz-Kersting

Abstract— **The users' mental state such as attention variations can have an effect on the brain-computer interface (BCI) performance. In this project, we implemented an adaptive online BCI system with alterations in the users' attention. Twelve electroencephalography (EEG) signals were obtained from six patients with Amyotrophic Lateral Sclerosis (ALS). Participants were asked to execute 40 trials of ankle dorsiflexion concurrently with an auditory oddball task. EEG channels, classifiers and features with superior offline performance in the training phase of the classification of attention level were selected to use in the online mode for prediction the attention status. A feedback was provided to the users to reduce the amount of attention diversion created by the oddball task. The findings revealed that the users' attention can control an online BCI system and real-time neurofeedback can be applied to focus the attention of the user back onto the main task.**

I. Introduction

BRAIN computer interface (BCI) systems translate brain signals into commands to control external devices [1]. The performance of these systems is influenced by the users' mental state such as attention variation [2]. However, the effect of these parameters has not been widely considered in previous studies and thus few BCI systems can be used in real-life situations [3]. According to our recent studies, the detection performance of BCI systems is degraded by the users' attention alterations and thus has a significant effect on plasticity induction that plays a critical role in designing of BCIs for neurorehabilitation [4-6]. The main aim of BCIs in the neurorehabilitation area is to help patients such as those suffering from Amyotrophic Lateral Sclerosis (ALS). ALS is a progressive neuro-degenerative disease which gradually causes a loss of muscle power and sever disability and finally death after 3-5 years.

Attention is the ability to select the target/relevant stimulus among various stimuli in our surrounding environment. Attention drift can happen due to external or internal sources. Dual-tasking which is referred to the execution of two tasks simultaneously is one of the external sources to divert the attention from one of the tasks (target task) and thus considered as distractor. Various EEG modalities may be used to monitor attention variations such as Event-related potentials (ERP), steady-state evoked potentials (SSEP) and movement-related cortical potentials (MRCP) [6, 7]. ERP components such as the P300 amplitude and latency are indicators of attention level as the P300 amplitude is enhanced and the corresponding latency reduced with increments in the attention. The MRCP is a slow cortical potential that commences approximately 2 seconds prior to movement onset and exhibits characteristics of movement preparation/execution [8, 9]. The MRCP was recently used to monitor attention alteration during movement execution as some of the temporal and spectral MRCP parameters changed with attention variations [4, 5].

In the current study, we aimed to design an adaptive online BCI system with changes in the users' attention. The current system provided a feedback to the users to focus the attention back to the main task (ankle dorsiflexion) when it was altered by an auditory oddball. EEG channels with superior classification accuracy were selected in the offline training mode of the system and applied in the online mode. In the online mode, the attention level of each single trial of dorsiflexion was classified as focused or diverted attention based on the attention level to the main task. In the case of diverted attention trials, a feedback was shown after movement execution to help participants to control their attention to the main task execution. It was hypothesized that the feedback can increase the attention to the main task and thus enhance BCI performance in the real-life situation.

II. Methods

A. Participants

Six ALS patients (4 males and 2 females; mean age of 60.6± 11.7) were included in this experiment. They should not be pregnant and also without sever cognitive impairments. The experiment was approved by the local ethical committee for the region Northern Jutland (62445).

B. Experimental setup

Twelve monopolar EEG channels were recorded using an active EEG electrode system (g. GAMMA cap[2], Austria) and g.USBamp amplifier (gTech, GmbH, Austria). The channels were placed on AF4, FC3, FC4, C3, Cz, C2, C4, CP2, P3, P1, Pz and P2. Bipolar surface electromyography (EMG) signals were recorded from tibialis anterior (TA) muscle.

Patients were seated on a comfortable chair one meter away from a digital screen while their hands placed on a table in the relaxed position. The experiment consisted two tasks, the

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main task was a motor movement execution (ankle dorsiflexion) timed with a visual cue while the cue included five main phases of focus, preparation, execution, hold and rest. After 2-3 s of focus phase (focus phase), the preparation phase started by a moving cursor (preparation phase). When a cursor reached to a ramp after 2 s, patients were asked to execute ankle dorsiflexion ballistic and powerful (execution phase) and hold it for 2s (hold phase). Participants could rest for 3-5 s after each movement execution (rest phase). In addition, an auditory oddball task was done based on the auditory tones played via a headphone. The auditory oddball contained four different tones of 700 Hz, 1200 Hz, 1700 Hz and 2200 Hz. All tones have the same probability of 25% as well as the same sound pressure level of 75 dB. Subjects were asked to count a target sequence of tones defined by the experimental operator as the secondary task. This task used to change the attention level to the main task and probe the brain.

The experiment consisted of three main phases of offline calibration, online phase with providing feedback to the participants and online phase without having the feedback. The offline phase had two blocks and one block belonged to each online phase. In all blocks, two types of trials applied, 'focused attention trials' included only execution of ballistic dorsiflexion while 'diverted attention trials' contained auditory oddball task in addition to the motor movement execution.

In the offline calibration, online with feedback and online without feedback block, 50 trials of focused or diverted attention in a random order with the same probability were performed. In the online with feedback block, a feedback according to the trial type provided to the participants. If the incoming trial classified as focused, a green bar appeared on the screen otherwise the color of the bar was red.

C. *Feature extraction*

Two types of features obtained by EEG temporal and spectral analysis. Twenty temporal features extracted from single trials of MRCP. Time and amplitude of negative peak, pre and post movement slopes, average of trial amplitude as well as variability attained in six time slots of [-2 -1] s, [-2 0] s, [-1 0] s, [-1 -0.5] s, [-0.5 0] s and [0 0.5] s with respect to the peak negativity.

Thirty spectral features were computed from the power of EEG signals in five main frequency bands of Delta (0.05-3 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-31 Hz) and Gamma (32-100 Hz). The power was obtained in the same time slots as the temporal features. Finally, fifty tempo-spectral features considered as the combination of temporal and spectral features.

The number of errors in counting of target sequence was considered as the performance criteria. Moreover, the difference between EMG onset and visual cue onset computed as the second performance factor.

D. *Offline and online analysis*

In the calibration phase which is the training phase for the online sessions, extracted features applied as the input of three types of classifiers, K-nearest neighbor (KNN), Support vector machine (SVM) and Decision Tree. Three channels with the highest accuracy as well as corresponding feature and classifier were selected to use further in the online mode.

In the online mode, the type of the trial was predicted according to the majority votes. If the majority of the selected channels (more than 2 channels) predicted focused attention trial, the trial type considered as the focused attention, otherwise the trial was classified as the diverted attention trial. In the online with feedback, a feedback was provided based on the prediction result.

E. *Statistical analysis*

Two-way Analysis of Variance (ANOVA) used for comparison of classification accuracy, true negative values (TN) which was the number of focused attention trials classified correctly and false negative values (FN) referred to the number of diverted attention trials classified as focused attention. Three experimental phases (calibration, with feedback and without feedback) and selected channels considered as two independent factors. Results were significantly different if $p<0.05$.

III. Results

A. *Performance results*

As illustrated in Fig. 1a, the number of errors in sequence counting increased from calibration to two online phases. However results of the ANOVA indicated that it is not a significant increment ($F_{(2,18)}=3.1$, $P>0.05$; calibration: 18.3±7.3, online phase without feedback: 19.6±8.3, online mode with feedback: 19.1±6.4).

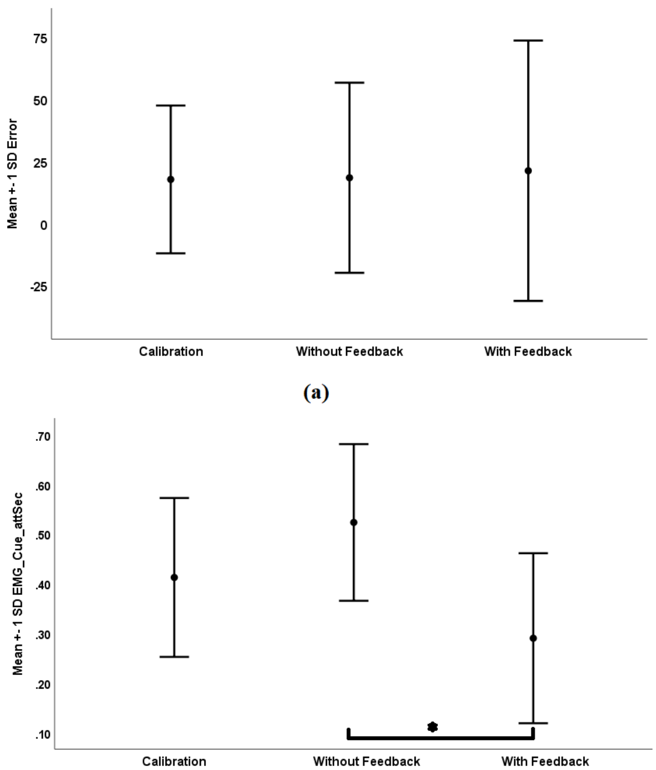
The time interval between EMG and cue onset was significantly lower in the with-feedback session compared to the without feedback phase ($F_{(2,18)}=3.9$, $P= 0.04$; calibration: 0.44±0.1 sec, without feedback: 0.48±0.1 sec, with feedback: 0.22±0.06 sec). These findings are also shown in Fig. 1b.

B. *Calibration results*

From the calibration phase, the three best channels with the highest accuracy as well as corresponding channels and classifiers from the calibration phase were selected. The results show that EEG channels placed on frontal and fronto-central lobes were selected more than the others with the corresponding spectral and tempo-spectral features. A sample of topographic power distribution is shown in Fig. 2 for one patient. Most power changes are related to the delta, theta and alpha band. Alpha band power decreased when attention was diverted while theta and delta power increased. Decision tree was the best classifier for most of the participants.

C. *Online results*

According to the ANOVA results, the classification accuracy was changed significantly among experimental phases of offline calibration, online session with feedback and online phase without feedback ($F_{(2,54)}=17.4$, $P<0.01$). Bonferroni *post-hoc* test showed that accuracy was significantly decreased from the calibration to with-feedback block (74.7±2.7% to 65.9±3.3%) and also between without feedback and with-feedback block (71.9±5.8% to



(a)

(b)

Figure 1. Illustration of **(a)** Average number of errors in sequence counting and **(b)** Average of differences between EMG and cue onset. Significant values shows with (*).

65.9±3.3%). TN values were also significantly different among experimental phases ($F_{(2,54)}$=14.4, P<0.001) while there was a significant decrement from calibration to with feedback (14.8±9.1 to 12.1±3.3) and also without feedback block (14.8±9.1 to 13.8±6.1). FN values revealed significant differences with regards to the experimental blocks ($F_{(2,54)}$=4.3, P=0.02) where this was increased from calibration to with-feedback and without feedback sessions (calibration: 4.9±2.6 with feedback: 7.7±2.8, without feedback: 6.4±3.2) .

IV. Discussion

Results presented here show that the users' attention level in a real-time BCI system can be controlled by using brain signals while attention to the main task was diverted with a secondary task. This has important applications in neurorehabilitaion and controlling of exoskeleton as attention to the task plays a key role in plasticity induction and increase the reliability of the system [10]

The calibration phase accuracy (74%) is supported by our previous work where we detected attention levels between focused and diverted attention conditions in the offline system (2). Although the accuracy in the online mode decreased compared to the calibration phase, these are still comparable with the recent work using auditory steady state responses to classify attention to different auditory stimuli (67%) [11]. The lower accuracy of the online system can be explained by the main aim of our work that was to reduce the attention drift by providing feedback. It means that we aimed to decrease the number of diverted attention trials and increase the focused attention trials. The number of diverted attention trials classified as the focused attention increase in the online phase with feedback (increment in FN) thus supporting this notion. On the other hand, TN values showed that the number of true classified diverted attention trails decreased significantly in the with-feedback session. So, we can conclude that feedback decreased the diverted attention trials and increased the focused attention to the main task as it was the main goal of the system.

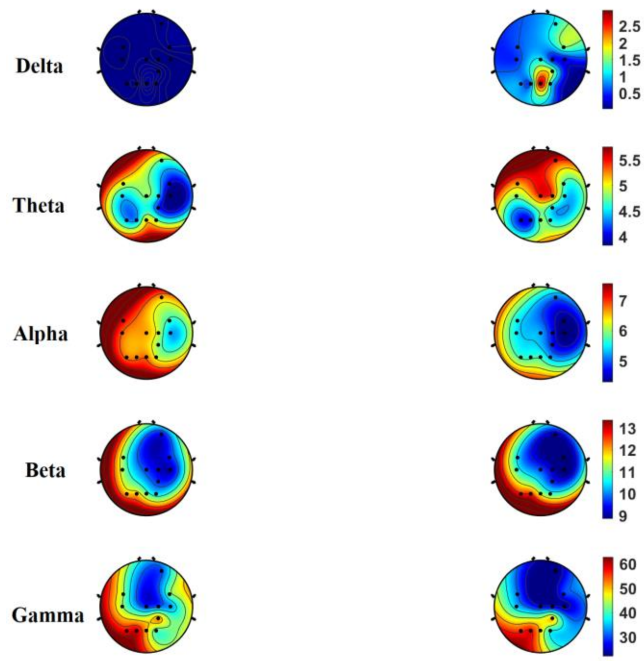


Figure 2. Illustration of power distribution in five frequency bands for one sample patient.

Temporal features obtained from the pre-movement phase of MRCP signals can decode movement parameters such as force and speed and also the users mental state such as attention variations [5, 12-14]. Spectral features obtained from five frequency band powers has been used in previous studies in EEG-based BCIs to classify baseline EEG from a mental task [15]. Based on the results of our work, tempo-spectral features represented better performance than the single group of features. This is supported by previous work using a combination of spectral and temporal features to classify attention level [4] and to detect movement onset [16].

The majority of the selected channels were located on the central and fronto-central lobe. This is supported by previous studies that used central channels for detection and classification of motor movements [17, 18]. It was also shown that attention to the objects can be classified in channels of Cz and Fz [19].

A. *Work limitations*

The main limitation that should be considered for the future works is the number of patients. It should be increased for the following steps. In addition, more EEG channels can be used to investigate the effect of attention diversion in various brain locations.

V. CONCLUSION

Here we investigated that attention diversion can be controlled by providing a feedback to the user. Such feedback has the potential to make BCI systems more robust and reliable and improve their performance in the real-life applications. This has an important implication particularly in the neurorehabilitation area aimed to help patient populations in their daily life and also to the rehabilitation exercise therapists.

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