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A Study on the Effect of Electrical Stimulation During Motor Imagery Learning in Brain-Computer Interfacing

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Abstract—Functional Electrical Stimulation (FES) stimulates the affected region of the human body thus providing a neuromuscular interface to non-recovered muscle groups. FES in combination with Brain-computer interfacing (BCI) has a widespread scope in rehabilitation because this system can directly link the cerebral motor intention of the users with its corresponding peripheral muscle activations. Such a rehabilitative system would contribute to improve the cortical and peripheral learning and thus, improve the recovery time of the patients. In this paper, we examine the effect of electrical stimulation by FES on the electroencephalography (EEG) during learning of a motor imagery task. The subjects are asked to perform four motor imagery tasks over six sessions and the features from the EEG are extracted using common spatial algorithm and decoded using a linear discriminant analysis classifier. Feedback is provided in form of a visual medium and electrical stimulation representing the distance of the features from the hyperplane. Results suggest a significant improvement in the classification accuracy when the subject was induced with electrical stimulation along with visual feedback as compared to the standard visual one.

Index Terms—Neuro-feedback, Functional Electrical Stimulation, Brain-Computer Interfacing, Common Spatial Patterns, Electroencephalography.

I. INTRODUCTION

The advent of Brain-computer interfacing (BCI) has opened a direct communication pathway between the brain and a peripheral device in form of robots, prosthesis, wheelchair or a computer without any muscle intervention. BCI has immense potential in facilitating rehabilitation for patients suffering from stroke, amyotrophic lateral sclerosis, spinal injury and physical disability [1]. A BCI system would drive a neuromuscular device to bridge the gap between the central nervous system and peripheral muscles, and in some instances even a separate prosthesis. Electroencephalography (EEG) is the most commonly used BCI recording device and signals related to limb movement (known as motor imagery signals) are elicited as Event Related Desynchronization/Synchronization (ERD/ERS) response [2],[3]. The BCI system decodes the ERD/ERS signals to determine the movement as intended by the user.

Functional Electrical Stimulation (FES) [4],[5] aims at directly stimulating the muscles which the patient is no longer able to use and it is reported that FES is capable of reconstructing certain daily life skills [6]. Studies in [6],[7],[8],[9] have shown that FES is capable of eliciting the recovery of skills such as standing up, grasping, cycling and walking. Most FES based rehabilitative system do not employ the cortical activity of the patient and only use peripheral learning to re-train the subject on his/her daily skills. A hypothesis on augmented movement therapy by FES exists which assumes that recovery occurs mostly due to cortical plasticity and partly due to peripheral mechanism [10] and it has been confirmed on motor learning tasks involving transcranial magnetic stimulation [11],[12] and functional magnetic resonance imaging [13].

Improvement in functional recovery through cortical plasticity can be attained if a coherence between the efferent neural activity (intentional efforts) and afferent neural activity (peripheral efforts) is developed. In this regard the FES activates the sensory channel which provides a maximal afferent inflow to the brain and the BCI would provide an effluent outflow of motor commands to close the motor loop [14],[15]. Thus, the rehabilitative system would work to improve the cortical and peripheral learning of the subject. Recently certain groups have explored this potential in implementing BCI in functional recovery using FES [16],[17],[18] to directly link the mental intention of the user with the muscular response. In such system, the BCI detects the motor intentions of the user which in turn activates the FES device. Pfurtscheller et al. were the first to restore hand grasp in a single case study by combining BCI with FES transmitted via surface electrode in [19] and an implanted stimulation system in [20]. Muller et al. in [21] studied the affects of FES on Steady-State Visually Evoked Potential (SSVEP) signal. Takahashi et al. in [22] have shown the presence of ERD/ERS patterns during an FES induced hand or leg movement tasks. A few studies also exist on the effect of FES learning in the performance of the BCI system. Gollee et al. in [17] found no major influence of FES on Steady-State Visually Evoked Potential (SSVEP) signal. Takahashi et al. in [18] also found no effect of FES on leg stimulation. Postohl et al. in [23] reported the improvement of angular accuracy of movements when the participants were provided with additional artificial proprioceptive feedback rather than using visual feedback but did not increase the overall accuracy determined from the average distance between the cursor and the target.

To date, in BCI experiments feedback is commonly provided...
electrical stimulation (ES) is transmitted to the subject during hand and foot motor imagery. In 3 of the 6 sessions, surface motor imagery and the second level discriminates between level hierarchy. The first level classifies between left and right trials for each task. The decoder designed in this work is a 2-

each task) and the last two sessions consist of 160 trials (40 trials for each task). The decoder designed in this work is a 2-level hierarchy. The first level classifies between left and right motor imagery and the second level discriminates between hand and foot motor imagery. In 3 of the 6 sessions, surface electrical stimulation (ES) is transmitted to the subject during the feedback period to aid the participant in performing the task. Thus, in this paper, we named the ES induced sessions as FES sessions and the sessions with only visual feedback as VIS sessions. In this paper, we want to study the effect of ES on the learning of the participants while performing a motor task and compare it with the standard visual motor task. A simplified block diagram of the our experiment is illustrated in Fig. 1.

Three healthy male subjects (2 right handed and one left handed), participated in this experiment. In this experiment, we abide by the norms of Helsinki Declaration of 1975, revised in 2000. Prior to the experiments, the subjects are informed about the purpose of the experiment and the tasks they have to perform.

A. Materials used

The EEG signals are recorded using a 14 channel Emotiv Epoc neuro-headset with a sampling rate of 128Hz and an in-built band-pass filter of 0.2-45Hz. The electrodes: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4, are arranged on the basis of the standard 10-20 system [27].

Surface electrical stimulation is relayed to induce wrist flexion and foot plantar flexion by applying the stimulation to the anterior compartment of the forearm for hand tasks and the triceps surae muscle group for the foot tasks. It is applied to each side of the hand and the foot, corresponding to the mental task to perform. The stimulus is delivered by a computer-controlled stimulator (ProStim, MXM, France) with pulse width (PW) modulation [28](PW max = 400 us) at a constant amplitude and frequency (20 Hz). Each stimulation sequence consists of a trapezoidal envelope train of PW (0.4 s ramp-up, 1.2 s plateau, 0.4 s ramp-down).

B. Design of the visual cue

The design of the visual cue for both FES and VIS sessions are the same. Each session starts with a baseline period of 20 seconds, during which the subject is asked to relax, followed by a repetition of trials. Each trial has the following cues: First, a fixation ‘+’ is displayed on screen for 1 second which is an indicator for the subject to get ready for the task ahead. Next, instructions of the motor task to be performed are provided to the participant for 1 second in form of arrows, in two separate cues of 0.5 seconds duration each. First, a left or right arrow is displayed on screen to indicate left or right motor imagery, respectively followed by up and down arrow which corresponds to hand and foot imagery, respectively. Following the instructions, the feedback is displayed on-screen, in the form of a blue bar, for 3 seconds. The subject starts performing the task on the start of this cue while simultaneously observing its feedback. For FES sessions, the ES is provided to the subjects at the onset of the feedback cue. For the training period, the feedback period of each trial is followed by a ‘+’ instead of the feedback bar. Lastly, a blank screen is displayed for 1.5s-3.5s for the participants to relax and avoid overlapping of the remnant EEG from the previous trial. A schematic time representation of the visual cue is illustrated in Fig. 2.

Fig. 1. Block diagram of our experimental setup during motor imagery sessions where user stimuli is provided with conventional visual stimuli and electrical stimulation, respectively.
C. Feature Extraction

Previous studies [1], [3], [29] on motor imagery suggests the presence of ERD/ERS in the $\mu$-rhythm (8-12 Hz) and central $\beta$ band (16-24 Hz). Thus, after acquisition, the raw EEG signal is band-pass filtered at 8-30 Hz using an IIR butterworth filter of order 5 and bandwidth of [8,30]Hz. This step removes the unwanted EEG information from the signal along with noise.

Prior to feature extraction, the training data of the participants is used to train the common spatial patterns (CSP). CSP [30] decomposes the raw EEG signal into spatial patterns extracted from two classes of single trial EEG. The patterns maximize the variation between the two classes. CSP was first applied for detection of abnormalities in EEG, followed by discrimination of EEG movement patterns by Ramoser in [30]. The design of the CSP is based on the simultaneous diagonalization of two covariance matrices which creates new time series signals optimal for classification. For $N$ channels of EEG for two classes, say, left and right imagery trials, the CSP algorithm creates an $N \times N$ projection matrix $W$ [30]. $W$ represents specific cortical activity during the motor tasks and with $W$, a trial $X$ is decomposed by

$$ Z = WX. $$ (1)

The variances for the two populations are largest in the first and last rows of $Z$ and thus, in this work, we select the first and last 2 rows (4 spatial filters) of $W$. Thus, the EEG data $X$ is filtered using the 4 spatial filters. Then, we calculate the variance of the 4 new time series for an epoch $T$

$$ \text{VAR}_p = \frac{1}{T} \int_{0}^{T} (Z_p(t))^2 \, dt. $$ (2)

Lastly, the variances are normalized and log-transformed to generate 4 feature vectors.

$$ f_p = \log \left( \frac{\text{VAR}_p}{\sum_{p=1}^{4} \text{VAR}_p} \right). $$ (3)

In this work, two CSP trainers are implemented: one for left-right imagery and the other for hand-leg imagery and the size of the epoch $T$ is 0.125 second.

D. Classification of the motor task

After feature extraction, the feature vectors are used as inputs to a linear discriminant analysis (LDA) classifier [31]. LDA aims at separating the data representing the different classes by constructing a hyperplane. Here, the class of an observation depends on which side of the hyperplane the feature vector lies. It assumes normal distribution of a data with equal covariance matrix for all classes. The separating hyperplane is a projection that maximizes the distance between two class means and minimizes the inter-class variance [31]. This technique is suitable for an online BC3 system because it has a low computational requirement and is simple to use. In this work, a hierarchical classifier is designed to perform multi-class classification among the four motor tasks. As shown in Fig. 3, the classifier first discriminates between left and right motor imagery followed by hand and foot imagery.

E. Neuro-feedback training

The classifiers produces two types of output after decoding: i) the output labels, and ii) the distance of the feature vectors from the hyperplane (hyperplane distance) as neuro-feedback to the participant. The neuro-feedback is displayed to the subject in form of a blue bar during VIS sessions and a combination of blue bar and electrical stimulation during

Fig. 2. A schematic time representation of the experimental task displayed to the participants.

Fig. 3. The 2-level hierarchical classifier designed for this experiment. The classifier first discriminates between left and right motor imagery followed by hand and foot imagery.

Fig. 4. An example of the feedback as visualized by the subjects. (a) shows an example of the right hand imagery which was classified correctly, while (b) shows an example of right hand imagery misclassified as right leg. (c) shows an example of left leg imagery which was classified correctly, while (d) shows an example of left leg imagery misclassified as left hand.
sessions for subject 1 is illustrated in Fig. 5. The topographical map is prepared from the interpolation of the vector present in the columns of $W^T$ of equation (1). From the left vs right imagery section, Filt1 of FES and VIS shows low activity in the FC6 region while Filt2 of FES has high activity in left hemisphere which is also shown in the VIS plot but in a lower scale. Filt1 and Filt3 show lower activity in the FC6 and FC5 region, respectively, which may indicate the presence of ERD in the contralateral region of left and right motor imagery, respectively. The same behaviour is also exhibited in the VIS sessions but less prominent than the FES ones. For hand vs leg imagery section, Filt3 of FES and Filt4 of VIS are mostly similar but the rest of the filters are distinctly separate from each other. It is noted in the figure that the VIS plots show higher activity than FES plots. Most patterns in FES and VIS show a common region of activation but FES plots show more specific regions of activation than VIS.

The extracted features are then fed to a trained LDA classifier to get the desired output, in our case, one of the four motor tasks. Table I provides the average results over the 3 FES and VIS sessions in terms of accuracy (acc), sensitivity (sen), specificity (spec) and information transfer rate (ITR) [31], [32]. Accuracy is a measure of how correctly a classifier can predict a class. Sometimes, the accuracy may provide a skewed result by detecting one class very well but the other class very poorly. Thus, the sensitivity and specificity provides a more reliable result in this context. Sensitivity suggests how good the decoder is to detect a positive class, while Sensitivity represents the amount of information reliably sent to the BCI system [32] and it is usually given by bits per trial (bpt). As noted from Table I Subject 1 shows a high increase in accuracy, sensitivity, specificity and ITR by 10.74%, 8.94%, 24.82% and 4.99 bpt, respectively while Subject 2 shows a mild increase by 2.5%, 8.33%, 12.98% and 2.34 bpt, respectively. On the other hand, subject 3 had a better performance during VIS sessions than FES sessions.

Next, we report the learning during FES and VIS session feedback for each trial. For this purpose, we measure the distance of the feature vector from the hyperplane for each epoch updated at every 0.125 seconds. We took this parameter to study the feedback effect because the larger the distance from the hyperplane, the higher is the confidence of the classifier to detect the right output. The average feedback curve for all the correctly classified trials of both FES (in blue) and VIS (in red) are shown in Fig. 6. From the curves we assume that greater
IV. CONCLUSION AND FUTURE DIRECTION

In this paper, we aimed at studying the effect of electrical stimulation on motor learning during BCI classification. Fig. 5 shows the spatial patterns during FES and VIS sessions and it is observed that most maps have a common region of activation. But more experimental sessions are required to reach a conclusive result to show a significant difference in the CSP patterns. Results on Table I also shows a significant rise in accuracy for Subject 1 and a mild increase of performance for Subject 2. The tabulated results suggests a positive influence of FES during motor learning of the subjects. The effective increase of learning during FES sessions are further validated from the results shown in Fig. 6. The FES sessions show a steady increase in learning as compared to the VIS session.

Visual feedback is the widely accepted form of feedback for such motor imagery tasks but the subject requires constant motivation to reach an optimal result. On incorporating electrical stimulation along with visual feedback the subjects in this experiment were reported to be more focussed in performing the tasks, especially for the longer sessions. Based on the results in this study, we can infer that electrical stimulation can also be used to improve the motor training of subjects and it can potentially provide better performance as it provides natural proprioceptive feedback related to motor performance than visual stimuli which requires user’s attention to visual feedback. Further studies on a larger group of subjects are required to validate this claim. Future studies in this research will include changing the intensity of FES during proprioceptive neurofeedback training to BCI based on the learning level of the subject. For example if a subject identifies left hand well and right leg imagery poorly, then the system will increase the intensity of FES during right leg imagery and decrease it during left hand imagery. This will lead to an improvement in motor imagery classification which would aid in neuroprosthetic or robot control [33].
REFERENCES