DETECTION OF INTENTION LEVEL IN RESPONSE TO TASK DIFFICULTY FROM EEG SIGNALS

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ABSTRACT

We present an approach that enables detecting intention levels of subjects in response to task difficulty utilizing an electroencephalogram (EEG) based brain-computer interface (BCI). In particular, we use linear discriminant analysis (LDA) to classify event-related synchronization (ERS) and desynchronization (ERD) patterns associated with right elbow flexion and extension movements, while lifting different weights. We observe that it is possible to classify tasks of varying difficulty based on EEG signals. Additionally, we also present a correlation analysis between intention levels detected from EEG and surface electromyogram (sEMG) signals. Our experimental results suggest that it is possible to extract the intention level information from EEG signals in response to task difficulty and indicate some level of correlation between EEG and EMG. With a view towards detecting patients' intention levels during rehabilitation therapies, the proposed approach has the potential to ensure active involvement of patients throughout exercise routines and increase the efficacy of robot assisted therapies.

Index Terms— EEG, BCI, LDA, sEMG, intention level, robotic rehabilitation

1. INTRODUCTION

Neurological injuries are the leading cause of long-term disabilities that restrict activities of daily living (ADL) of millions of patients. Physical rehabilitation is the major form of treatment for neurological disabilities helping patients regain their motor control and actively take place in society. As rehabilitation therapies are known to be more effective when they are repetitive, intense, long term and task specific; manual administration of such therapies becomes costly due to the physical burden and the manual labor involved.

Since active participation of patients in the therapies is known to be crucial for motor recovery, brain-computer interface (BCI) technology promises to become one of the main pathways to guide rehabilitation protocols to effectively induce activity-dependent brain plasticity and to restore neuromuscular function. In particular, [1–3] have shown that stroke patients are capable of operating BCI systems as efficiently as healthy subjects, while in [4, 5] EEG based BCIs have been integrated with robotic systems for rehabilitation. Patient trials with these system provide evidence that these systems can be effective in restoring motor functions of upper extremities.

In the BCI-based rehabilitation systems mentioned above, patients' intentions are only used to trigger the system, to start or to stop the movement without considering the continuity of patients' focus during the course of the task. Consequently, these systems cannot ensure active participation of patients in the movement therapy because regardless of whether the patient spends more or less effort to be involved, the resulting movement is always the same. Hence, it is of interest to develop techniques that can infer the intention level of subjects in the course of a robotic rehabilitation routine.

In the literature, various techniques have been proposed to ensure active participation of patients in rehabilitation therapies by using surface electromyography (sEMG) signals as a means to provide driving signals to control rehabilitation devices. EMG signals are preferred as the human-robot interface for patients with remaining muscle functions, since these signals can directly correlated with human intention and provide fast enough reactions for adjusting amount of assistance [6–8]. In many implementations, the amount of assistance provided by the robotic device is taken to be directly proportional to the difference between the weighted functions of sEMG signals recorded from antagonistic muscle groups, reflecting the users' movement intention [9, 10]. Moreover, the linear envelope of sEMG signals is used as an approximate estimation of joint torque, since it represents the muscle activation level and direction of intended movement coherent with the action of limb [11, 12]. Linear envelope of sEMG signals is advantageous since this method does not require much effort to precise calibrate the relation between the EMG intensity and joint torque, as necessitated in the other approaches [9, 10], but instead provides simple and sufficiently accurate means of torque estimation. Unfortunately, since remaining muscle function is a prerequisite for EMG based ap-

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proaches, these techniques are not applicable to patients with severe disabilities. BCI-based systems provide a viable alternative.

Recently, there have been studies to infer the subject's level of mental stress, conditions or emotions from EEG signals. [13] proposes an approach to incorporate the user's attention state into game control, by computing the short window energy of the EEG signals that contrasts between attention conditions in which the subjects were asked to perform Stroop tasks and in-attentiveness conditions in which they were instructed to relax. [14, 15] present a study to find a correlation between emotions and chronic mental stress levels measured by Perceived Stress Scale 14 (PSS-14) and EEG signals. [16] proposes a fast emotion detection approach from EEG, by showing neutral, positive and negative video clips to the subjects. Immediately after the played video, the subjects reported the induced emotions during watching the video clip. But these proposed approaches are very specific to the tasks executed in the experiments, strongly dependent on the patients or not suitable for online asynchronous control of robotic rehabilitation systems.

On the other hand, in rehabilitation therapies, as patients are always asked to finish a task by means of imagery or real movements, the velocity of the executed or imagined task may also be correlated with the patient's intention level during the task. In [17], each subject was asked to perform elbow flexion/extension motions for three minutes with arbitrary angles and speeds. The experimental results suggest that EEG signals with the tested decoding model can be used to continuously decode the elbow joint velocity. [18] shows an attempt to decode hand movement speeds from EEG signals during a drawing task. In [19], a linearly correlated relationship between speed and the EEG activity in the alpha and beta frequency bands during imagined and executed hand movements is found. In [20], we have presented a method that uses posterior probabilities extracted from an LDA classifier as levels of "intention" and controls the speed of a rehabilitation robot, providing useful feedback to subjects to encourage their active participation to complete the task, according to these intention levels. But the validation of posterior probabilities obtained from the EEG signals as accurate measures of instantaneous intention levels of motor imagery during the movement, has not been performed.

The main contribution of this paper is an approach that enables detection of intention level of subjects in response to task difficulty based on their EEG signals. In particular, healthy volunteers are asked to relax or execute right elbow flexion followed by extension movements while lifting one of 3 different weights by their right hands. As the weight increases, subjects need to try harder to lift the heavier load. In the proposed method, LDA is used to classify ERD/ERS patterns of different problems corresponding to classes of lifting periods with "load 1", "load 2", "load 3" and resting periods. Moreover, a supplementary study is also presented for the validation of the intensity level obtained from EEG signals, by applying a correlation analysis with corresponding sEMG signals. Our preliminary classification results suggest that it is possible to classify EEG signals generated during the process of lifting different weights. Indicating the intention level of patients, a BCI-based robotic rehabilitation protocol based on the ideas proposed here might have the potential to ensure active involvement of patients with severe disabilities in therapeutic exercises and increase the efficacy of robot assisted therapies.

The paper is organized as follows. Section 2 describes the BCI component. Section 3 provides the first experimental paradigm, including the EEG data collection procedure and details of EEG feature extraction and classification methods. Section 4 presents the second experimental paradigm including EMG data collection procedure, details of EMG feature extraction, the EMG-EEG correlation analysis and EEG classification results. Finally, Section 5 concludes the paper and discusses future work.

2. BCI SYSTEM

BCI generates commands from the brain signals measured by invasive or non-invasive methods. Although the invasive method results in more accurate signals, the non-invasive method is obviously more practical and safer for the subjects. Moreover, the non-invasive method is easy-to-use and low-cost. The main purpose of non-invasive EEG-based BCI is to measure the electrical activity using EEG signals and to classify their patterns to extract user's intention. Underlying patterns of EEG signals measured in experiments designed to emphasize sensorimotor rhythms related to the user's intent, can be automatically recognized by using ERD/ERS phenomena [21, 22], where ERD is related to the motor tasks and ERS is related to the passive states.

In the BCI system designed for this study, a trial consists of a passive period followed by an active period with a cue. At the beginning of a trial, an acoustic stimulus indicates the beginning of a trial and then a cross '+' is displayed for 6 seconds which indicates a passive period. Then, a right arrow or 'Relax' text appears as a cue for 6 seconds. Therefore, the length of each trial is 12 seconds as shown in Figure 1. The right arrow cue indicates the subject to execute right elbow flexion followed by extension and the 'Relax' cue orders the subject to relax (see Figure 2). The order of the cues is random and a session consists of 3 runs with 20 trials (10 trials for right arm movement and 10 trials for relax).

Fig. 1. Timing scheme

Fig. 2. Interface used in the experiments

3. EEG EXPERIMENTS

A cue-based synchronous offline experiment consisting of 3 consecutive sessions with resting periods between each them to avoid fatigue, was designed to detect the intention level in response to task difficulty, from EEG signals. The task of the subjects is to relax or execute right elbow in fully flexed position followed by extension movements while lifting loads of different weights by their right hands according to the cues shown in the interface. The first session involves flexion and extension movements without any load. In the second session, the subject lifts a dumbbell when asked to execute right arm movements. For the third session, the weight of the dumbbell is increased. The weight of the lifted loads varies between $1280 - 7280$ g depending on the subject's skeletal muscles' maximum power output.

3.1. EEG Data Collection

For EEG recordings, a Biosemi ActiveTwo EEG System is used. The recording configuration shown in Figure 3 uses Ag-Cl electrodes at C_3, C_z, C_4 locations of the international 10-20 electrode placement system, at 512 Hz sampling rate. Their anterior and posterior channels are used as references. By subtracting the average of the data received from anterior and posterior channels of a channel, three referenced main channels are obtained.

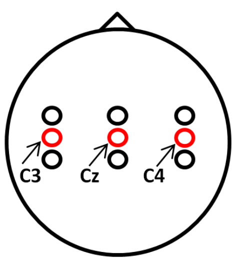

Fig. 3. Positions of the electrodes used in our experiments.

3.2. EEG Data Analysis

EEG in motor-task experiments is typically characterized by its rhythmic activities detected by using the phenomena of ERD/ERS [21, 22] patterns introduced in 1990s. In the case of execution of motor movements, ERD or ERS occur and change the amplitude of the signal where ERD is related to the motor tasks and ERS is related to the passive state. In this study, ERD and ERS are mainly characterized by the help of spectral powers computed in the typical EEG $alpha$ ($\alpha,\ 8 - 13Hz$), $sigma$ ($\sigma,\ 14Hz - 18Hz$), $beta$ ($\beta,\ 16 - 24Hz$) and $beta_2$ ($\beta_2,\ 24 - 30Hz$) frequency bands related to the preparation of the movements. To analyze these frequency bands the Short Time Fourier Transform is applied to each trial. The activity of the brain can be observed after the cue is shown. Hence, instead of analyzing frequency bands of the entire signal, a timing window is used. Afterwards, the average power spectral densities of the 3 selected frequency bands are calculated and selected as features. Therefore, 4 different spectral power densities are calculated for 3 different electrodes resulting in a 12-dimensional feature vector.

In this work, LDA which is a fast, stationary classification method is used to classify motor movements using the extracted features [23]. The performance of the LDA classifier is measured by applying two-fold cross validation for 300 times to obtain different training and test data sets with consisting of the 75% and the 25% of the entire data, respectively. Overall classification accuracy is obtained by averaging over these 300 classification experiments.

The first classification problem is built separately for each session to classify right arm movement periods vs. resting periods. In the second classification problem, each session is classified against each other (load 1 vs load 2, load 1 vs. load 3, load 2 vs. load 3). Finally, the third classification problem contains 3 classes (load 1, load 2, load 3) and tries to find which load was being lifted during the trial. We note that load 1 indicates no load; load 2 is the lighter load, and load 3 is the heavier load.

Right handed 2 female subjects, aged 23 and 25, have participated in this study. The classification accuracies obtained are listed in Tables 1, 2 and 3. For this experiment, β is found as the most informative frequency band. Therefore, the classification results where only the power spectral density of β is used as the feature, are also presented. The results show that movement periods can be detected successfully and the intention level of the subject in response to task difficulty may be extracted from the EEG signals with promising accuracy. Note that results in Tables 1 and 2 correspond to a two-class problem, whereas those in Table 3 correspond to a three-class problem.

Session	Frequency	Subject A	Subject B
1	all	79.64	83.43
	β	82.10	78.55
2	all	83	79.60
	β	85.38	78.29
3	all	88.22	87.36
	β	89.60	86.21

Table 1. Classification accuracies of the first classification problem (load vs. relax) of the EEG based experiments.

4. EEG AND EMG EXPERIMENTS

EEG classification experiments in Section 3 have provided evidence that the EEG signals contain information about mo-

Load	Frequency	Subject A	Subject B
1 vs. 2	*all*	58.64	55.31
	β	64.62	63.90
1 vs. 3	*all*	88.31	79.05
	β	94.32	73.19
2 vs. 3	*all*	80.90	78.95
	β	89.45	79.52

Table 2. Classification accuracies of the second classification problem of the EEG based experiments.

Frequency	Subject A	Subject B
all	62.92	60.59
β	69.83	61.11

Table 3. Classification accuracies of the third classification problem of the EEG based experiments. This is a three-class problem.

tor task difficulty. In this section, we consider a slightly different experimental set up, and not only run similar classification experiments to Section 3, but also provide an alternate evaluation mechanism to explore the same question. In particular, we exploit (and also verify) the well-known direct relationship between rectified sEMG signals and the weight of the load, and evaluate the correlation between simultaneously recorded EEG and sEMG signals. In this experiment, subjects are asked to execute flexion and extension movements where the elbow flexion is limited to 30° as shown in Figure 4. The angular limit in the elbow flexion plays an important role in the accuracy of the sEMG signal validation.

In this experiment, sEMG signals are collected simultaneously with EEG signals, from the biceps branchii, which is the muscle that lies on the upper arm between the shoulder and the elbow, with the aid of surface electrodes of a sEMG signal acquisition device (Delsys-Bagnoli-8). In particular, raw sEMG signals sampled at 1 kHz (using NI USB 6251) are filtered against inherent environmental noise and artifacts with a band-pass filter with a passband of 20-500 Hz. Then, these signals are full-wave rectified. The full-wave rectified signals are later utilized to extract the relation between the force exerted by the muscle and the intensity of sEMG signals.

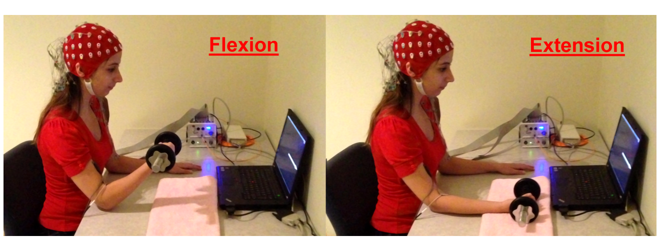

Fig. 4. Elbow flexion of 30° followed by extension.

4.1. EEG Data Analysis

Right handed 3 subjects (1 male, 2 females), aged 23-31, have participated in the EEG-EMG experiments. The same classification problems presented in Section 3.2 are analyzed and the accuracy results are shown in Tables 4, 5 and 6. These results support the inferences of Section 3.2.

Session	Frequency	Subject C	Subject D	Subject E
1	*all*	62.43	53.64	69.17
	β	59.38	53.64	65.62
2	*all*	71.72	60.45	74
	β	76.67	72.21	59.86
3	*all*	84.69	61.95	66.64
	β	83.23	64.69	71.03

Table 4. Classification accuracies of the first classification problem of the EEG-EMG based experiments.

Load	Frequency	Subject C	Subject D	Subject E
1 vs. 2	*all*	60.98	75.19	67.14
	β	70.74	77.31	64.12
1 vs. 3	*all*	84.46	76.36	76.26
	β	78.64	77.82	73.82
2 vs. 3	*all*	75.69	78.90	65.67
	β	60.74	74.21	68.15

Table 5. Classification accuracies of the second classification problem of the EEG-EMG based experiments.

Frequency	Subject C	Subject D	Subject E
all	54.65	63.37	49.85
β	52.017	68.45	49.84

Table 6. Classification accuracies of the third classification problem of the EEG-EMG based experiments. This is a three-class problem.

4.2. EMG Data Analysis

The RMS value of the sEMG signal is correlated with the level of physiological activities in the motor unit during muscle contraction. Hence, four different features were extracted from the RMS value of sEMG signals to reflect the properties of the muscle activation level depending on the executed task [24]. In particular, the maximum, sum and energy of the data inside the window containing the $3000^{th} - 5000^{th}$ samples $(5.9 - 9.8s)$ and the energy of the 1500 samples centered around the maximum point of the EMG in a trial were used as the EMG features. In Figure 5, the means and the standard deviations of each feature calculated from the sEMG of $Subject\ D$ and their p-values obtained from a t-test are shown. The increasing value of these features as a function of task difficulty indicates the positive correlation between the two, which is an expected behavior.

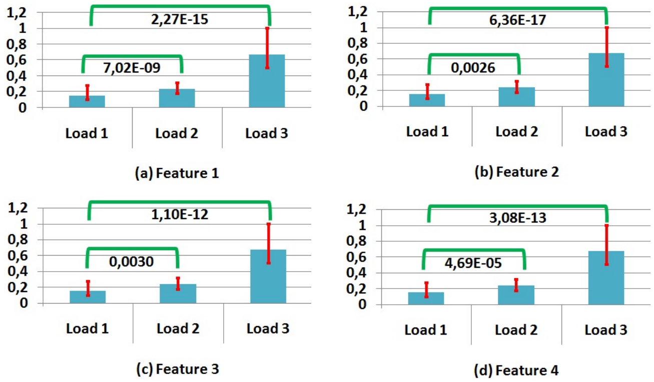

Fig. 5. EMG features and p-values of Subject D: (a) Maximum, (b) sum, (c) energy of the signal between the $3000^{th} - 5000^{th}$ samples, and (d) energy of the 1500 samples centered around the maximum point of the EMG in a trial.

4.3. Correlation Analysis

Given the well-known relationship between the EMG signals and task difficulty, we are now interested in analyzing the correlation between features extracted from EEG and EMG signals. This analysis is aimed at supplementing our EEG classification experiments, which have already demonstrated that EEG signals are informative about intention levels of the subjects in response to task difficulty. The EEG-EMG correlation study provides an alternate analysis. The correlation coefficients for each of the EMG features were calculated for each frequency band, electrode and subject. The mean correlation coefficients across the EMG features for each subject are shown in Figure 6a and across the subjects for each EMG feature are presented in Figure 6b. We observe that the correlation between the EMG features and the EEG features from the C_3 and C_z channels are consistent for each subject and for each EMG feature.

5. CONCLUSIONS

In this study we considered the question of whether EEG signals can provide information about the intention level of a subject in a motor task experiment in response to task difficulty. This is motivated by the desire to exploit information about the level of intention of patients in BCI-based robotic rehabilitation. We designed two distinct data collection experiments involving different levels of elbow flexion and extension movements. Each experiment contained sessions dedicated to lifting loads of different weights, leading to varying levels of task difficulty. We collected EEG data using a cue-based synchronous set up, where subjects were asked to rest or to execute right elbow extension and flexion movements while lifting various weights. We used LDA to classify the ERD/ERS patterns. We posed several two-class and

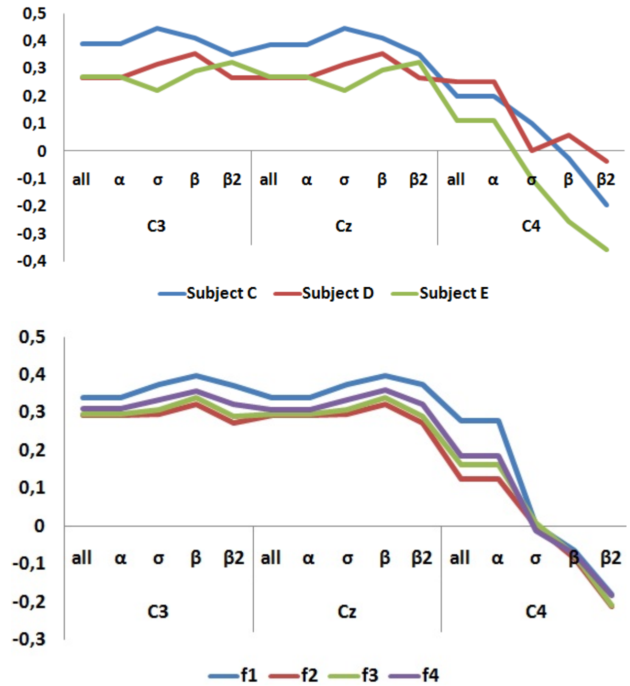

Fig. 6. Correlation analysis: (a) The mean correlation coefficients across the EMG features for each subject, (b)the mean correlation coefficients across the subject for each feature.

three-class classification problems, where classes correspond to task difficulty (weight of the load lifted) or indicate a relaxation interval. Our experimental results suggest that it is possible to extract information from EEG signals about the intention level of the subjects in response to task difficulty. In the second experiment, we collected EMG data in synchrony with the EEG data as well. Since EMG data are known to capture information about task difficulty in a motor task execution experiment, we also examined the information content of the EEG signals about task difficulty by analyzing the correlation between features extracted from EEG and EMG signals. Our results indicate some level of correlation between the two types of signals. Future work could involve a comprehensive analysis of the mutual information of EEG and EMG signals.

Our planned future work includes the control of a robotic rehabilitation system using the intention levels obtained from the EEG signals. Using intention levels extracted from EEG rather than binary classification outputs (characterizing simply the intention to move or not) provides various opportunities in a rehabilitation protocol. In particular, one can adjust the exercise speed, difficulty or assistance level based on the instantaneous intention levels. This might offer the potential to increase the efficacy of robot assisted therapies by ensuring active involvement of the patients in the process.

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