Classification of Motor Task Execution Speed from EEG Data

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***Abstract*—It is believed that the obtention of instantaneous intention level from electroencephalogram (EEG) signals and its use as a control signal may increase the benefits gained from the robotic rehabilitation process of stroke patients. This paper investigates a method for classifying the speed of arm movements from EEG recordings of healthy subjects under the assumption that the intention level of a patient may be reflected in motor task execution velocity. Experimental data were collected from eight (four male, four female) healthy volunteers while they were performing right arm movements at two different speeds. We designed an experiment in which the subjects were asked to carry a glass cup in two different environments: nail or cotton. The task speeds for both environments were decided individually by the volunteers; however the nail environment had a maximum speed limit. Participants were warned by a crashing glass audio stimulus if they exceeded the speed limit of the nail environment. As a result, a simple daily life activity was performed at two different speeds as an experimental task. Based on experimental data from eight healthy subjects, we successfully classified two different speed levels and resting state from event related synchronization (ERS) and event related desynchronization (ERD) patterns of EEG signals by linear discriminant analysis (LDA) classifier. Results reveal that LDA can discriminate different velocity levels when six frequency bands of three EEG recording channels were used as the feature vector.**

***Index Terms*—BCI, EEG, intention level, robotic rehabilitation, motor task.**

I. Introduction

One of the most common reasons of long-term disability is paralysis which may result from traumatic injury, stroke, or amyotropic lateral sclerosis (ALS). Although the cognitive brain activities of these patients remain intact, they lose voluntary muscle control and suffer from communication problems. The idea of utilizing brain signals instead of muscular activities has motivated work on brain-computer interfaces (BCI). BCIs aim to maintain activities of daily living of patients by creating a new channel from brain to computers without any muscular control. BCI systems use brain signals as input and convert these signals to meaningful outputs in order to provide control over the external environment. Particularly, the discovery of EEG similarities between motor imagery and execution has given hope to stroke patients [2], [3]. Besides the benefits on locked-in patients, recent studies have shown that BCIs have the potential for significantly positive effects on stroke rehabilitation protocols. The studies in which the movement of the patients were supported by an external device when event related synchronization (ERS) or event related desychronization (ERD) are detected on EEG signals suggest that BCI supported rehabilitation protocols have a great potential of improving conventional rehabilitation protocols [4]–[9].

Another main application domain of BCIs is external body skeleton systems in which EEG signals of users are decoded and converted to meaningful information to perform natural movements and execute motor tasks, replacing the limbs of the patient. For instance in [10], when electooculography (EOG) signals of a subject are focused on a target, a Kinect sensor scans the corresponding area and detects the target object. If ERD is detected on EEG signals, the exoskeleton grabs the target and brings it to the subject. Even though the performance of the system is not argued to be at the desired level yet, it is promising for many people who are suffering from ALS.

In [11], healthy volunteers were asked to imagine wrist extension and rotation at two different speeds (i.e., fast or slow); where fast means as fast as possible, and slow refers to completing the movement in 3 seconds. Movement type was not successfully classified with EEG features in this study; whereas, the speed level was classified with significant accuracy. Moreover in [12], a similar experimental procedure was tested on four paralyzed ALS patients. Although the accuracies in this study were lower than [11], it was claimed that healthy subjects perform better at movement imagination because of unharmed motor function pathways. Additionally in [13], classification movements that require different intention levels from EEG data were analyzed in a different way. Healthy volunteers were asked to lift different weights while their EEGs were being recorded, and EEG signals corresponding to different task difficulties were classified.

We designed an experiment in which subjects performed a one-dimensional right arm movement in two conditions: 1) as fast as permitted by their body limit, 2) as fast as the experiment protocol permits. Eight healthy volunteers participated in this study. A potential disruptive fatigue effect is prevented by the horizontal design of the experimental setup. Power spectral densities of channels are averaged at six frequency bands and 18-dimensional feature vectors are classified by applying linear discriminant analysis (LDA).

The main motivators of this study can be divided into two parts. First, we aim to improve the effectiveness of BCI-assisted exoskeletons as in [10]. In real world, we determine our movement speeds according to the tasks that we perform. For instance, if we drink a cup of hot coffee, we behave more carefully; however, we might hurry up while taking our mobile phone before leaving home. Hence, detecting the intention to move fast or slow can be used directly adjust the speed of a BCI-assisted exoskeleton. Moreover, we propose a more realistic design than those in literature. In our experiment, movement speed is implied by the required carefulness for the task, rather than dictating a movement at a particular speed. Second, a new approach is presented to the detection of intention level problem which is evaluation of intention in response to task velocity using EEG-based BCI. Consequently, we develop a methodology for speed estimation from EEG signals, design an experiment which resembles the activities of daily living and come up with an approach to detect intention level.

In the following section, the methodology including subject properties, data acquisition, experimental procedure, feature extraction and classification technique are explained. The experimental results are given in Section III. Section IV provides discussion of results and future directions; while Section V summarizes the conclusion.

II. Materials and Methods

A. Subjects

Eight healthy volunteers aged 26-36 years (four male and four female; mean age: 26.68 ± 4.4 years; all right handed) participated in the study. None of the subjects had any known motor diseases on their right arm or psychological disorders. Before the experiments, experimental procedure was explained to all participants and their informed consent were taken.

B. Data Acquisition

EEG records were collected by a Biosemi ActiveTwo EEG System located at the Sabanci University Computer Vision and Pattern Analysis Laboratory. EEG was recorded from Ag-Cl electrodes at $C3$, Cz and $C4$ locations of the international 10-20 electrode placement system at a sampling rate of 512 Hz. The upper and lower neighbor channels ($Fc3$, Fcz, $Fc4$, $Cp3$, Cpz and $Cp4$) were recorded in order to reference channels $C3$, Cz and $C4$. The mean value of lower and upper channels were subtracted from the central channel, as given in (1):

$$x_1 = x_{C3} - \frac{x_{Cp3} - x_{Fc3}}{2} \tag{1}$$

where x_1 is the first referenced channel value and x_{Cp3} is the recorded value of channel $C3$.

C. Experimental Procedure

In this experiment, the interaction between the subject and the virtual environment is realized through a haptic interface. The haptic environment is rendered on a linear actuator (ServoTube Linear Actuator, Copley Controls) endowed with a position encoder, designed by means of an impedance control scheme and rendered in real-time with a sample rate of 500Hz. Subjects participate in the linear haptic interface with the aid of a purposely designed apparatus. The apparatus is intended to fix the subject's arm to the haptic environment by preserving a potential angular deviation at wrist joint in such a way that the forearm and the hand are able to move as a whole. During the experiment, subject's forearm is constrained to be perpendicular to the upper arm and kept parallel to the ground. While executing the defined task, instantaneous position state of the limb gathered by using the encoder, velocity state and human effort described by the exerted force level are transmitted to the digital environment via DAQ converter (Quanser-Q8 usb).

Subject's motivation to execute the task is enhanced by means of the virtual environment. Visual and auditory feedbacks helps subjects learn to regulate their limb speed based on the task. Subjects are expected to concentrate on the speed of their limb and canalize their EEG signals for one type of challenge, that is regulating proper velocity level. Hence, the mechanical impedance of the haptic environment is empirically set in such a way to simulate a natural environment such as fresh air, to avoid performing a task that is more than desired. The haptic device is responsible for preparing the appropriate mechanical and environmental conditions. In particular, subjects feel how much effort they spend while resisting against the mechanical impedance during a motion of one point to another. The consequence of the interaction of the limb with the nail or cotton surfaces is visually and auditorily provided to the subject without feeling interaction force at hand. By doing so it is hypothesized that subject needs to focus on task more to execute it accurately, which improves the intention level of EEG signal.

The subjects were seated on a chair wearing an EEG cap while the left arm was at rest and the right arm was located on a stabilizer handle. Since stronger movements are more distinguishable on EEG and wrist is more susceptible to fatigue, the subjects pushed the handle from their right shoulder [15]. They were warned not to use any body or hand movement during the recording, and the undesired wrist movements were blocked by a wrist splint as shown in Figure 1. According to the scenario, they carried a glass cup towards two different types of wall which were made either of nail or of cotton. In the virtual environment, there were a glass cup figure on the right side and an environment specifier figure on the left side which was either a bed of nails or a piece of cotton, as shown in Figure 2. The glass cup figure on the right moved left while the subject was sliding the handle to left. When the glass cup reached the wall, the subjects were given 2 seconds to return the handle to the starting point back at right end. The number of succeeded trials was shown at the top of the screen.

At the beginning of each experiment the subjects participated in a pre-flight session in which they heard a broken glass sound if they carried the glass cup too fast towards the nail wall. No data was recorded at this time. The subjects were free to move at any speed in cotton; whereas, the limit was 60 mm/s for nail environment. Immediately after the pre-flight session, the experiment that involved nine sessions started. Each session had two sub-sessions in which both of

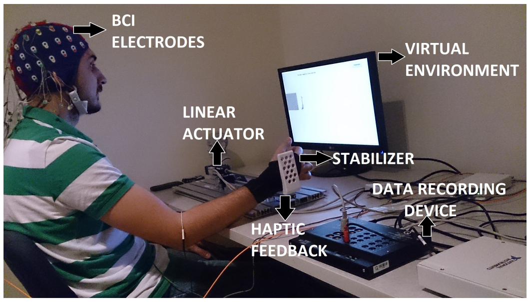

Fig. 1: Experimental Setup.

Fig. 2: Virtual Environment.

the environments were experienced once for 30 seconds. After each 30-second period, EEG was recorded for 10 seconds (the resting state) in which they were not allowed to move so that the resting states could be classified as well. There was a relaxing session for 10 seconds in between each sub-session, in which the subjects were free to move. Therefore, the possible tags for a signal sample were nail, cotton, rest or relax, and all samples were labeled by these tags throughout the experiment. Figure 3 illustrates the flowchart of a session that occurred 9 times throughout an experiment. The order of the environments was assigned randomly in order to avoid any fatigue effect.

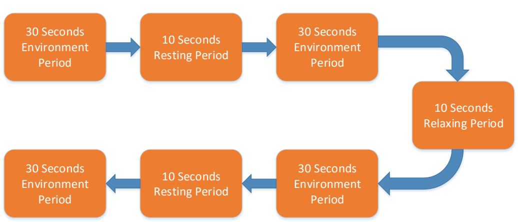

Fig. 3: Experimental Flow.

D. EEG Pre-Processing and Feature Extraction

The collected dataset contained samples labeled by either environment type (i.e., nail or cotton) or the experiment stage (i.e., rest or relax). Each session data was detrended. Additionally, the samples in the nail environment were labeled as unsuccessful if the speed limit was exceeded, and as successful otherwise. For data cleansing, the unsuccessful samples were removed from the dataset. By nature of the experiment, the success of each trial was evaluated based on the final velocity of the carrying process. Due to the acceleration phase at the start of each trial, we considered only the last 2000 (approximately 4 seconds) samples of each trial for classification. In Table I, the numbers of successful trials for each condition of all subjects are given. Since the speed of each trial was determined by the subject, trial numbers of each condition change for all subjects.

TABLE I: Number of Successful Trials of Subjects.

Conditions	Successful Trials							
	S1	S2	S3	S4	S5	S6	S7	S8
Nail	88	79	124	81	68	150	106	116
Cotton	115	124	143	91	98	150	115	124

Frequency band powers in six main bands in the typical EEG signal; delta (δ, 0.1 Hz-5 Hz), theta (θ, 5 Hz-8 Hz), alpha (α, 8 Hz-12 Hz), sigma (σ, 12 Hz-16 Hz), beta1 (β1, 16 Hz-24 Hz) and beta2 (β2, 24 Hz-30 Hz), were computed using the short time fourier transform (STFT) for characterization of the ERD and ERS [14]. STFT was applied to each trial with a 128-sample window. The window was shifted by 16 samples in each step to calculate the power spectral density. This process was repeated for all three channels and six frequency bands. Consequently, a 18-dimensional feature vector was composed for each evaluable trial.

E. Classification

At the classification step, 18-dimensional feature vectors of all successful trials from all nine sessions were gathered and separated as training (75%) and test (25%) data. This process was repeated 300 times for cross-validation and at each repetition a new LDA model was generated so that the selection of training and test data was diversified. The presented results are the mean value of 300 recurrences. Although there are many different classification methods, LDA is applied in this study owing to its utility in terms of speed and stationarity [16].

III. Results

Single-trial classification results of velocity of right arm movements from EEG recordings for 8 volunteers are calculated for nail vs. rest, nail vs. cotton, cotton vs. rest and nail vs. cotton vs. rest conditions. The performance, namely the classification accuracy values, are given in Table II for all subjects and all classification problems. In the table, the first column represents the nail vs. rest classification and the mean accuracy for 8 subjects is 64%; while the second column contains the results of a relatively harder classification problem which is cotton vs. nail. Since both of the classes require movement, albeit at different speeds, this more challenging problem results in lower accuracies. The classification results of the fastest task vs. resting task is given in the third column.

IV. Discussion

In this study, the nail and cotton environments are distinguished with 59% accuracy; while classification performances of these two cases from resting state are higher. In particular, the results for some subjects show that high classification accuracy can be achieved -especially in nail vs. rest and cotton vs. rest conditions. For instance, nail vs. rest comparison of

TABLE II: Experiment Comparison Results.

Results	Comparison Classes			
	Nail-Rest	Cotton-Nail	Cotton-Rest	Cotton-Nail-Rest
Subject 1	76	63	66	53
Subject 2	59	64	73	52
Subject 3	50	64	64	66
Subject 4	65	59	63	53
Subject 5	69	56	71	51
Subject 6	70	58	69	63
Subject 7	60	54	69	44
Subject 8	63	57	60	67
Average	64	59	67	56

Subject 1 has an accuracy of 76% and cotton vs. rest of Subject 2 is 73%.

Since the fastest movements were executed in the cotton environment, the highest accuracy levels are obtained in cotton vs. rest comparison with 67%. Moreover, the comparison of two active sessions with resting state (i.e., nail vs. rest and cotton vs. rest) provide higher results than nail vs. cotton comparison, as expected.

The average result given in the last column shows that the comparison of all classes can be accomplished by 56% accuracy. Particularly, the results of three subjects (Subject 3, 6 and 8) are quite satisfactory. This three-class case involves the most worthwhile result of this study for assistive robotic applications because it presents the precision of the robot's decision when the robot faces a three class problem (i.e., rest, move fast, or move slow). Since the results are significantly higher than chance level for a three-class comparison (33%), one can suggest that it is possible to determine whether the robot moves or not and the movement velocity with a reasonable accuracy.

Despite the fact that it is possible to detect differences of these two similar classes, the accuracy is still not very high. One further step could be to extend the analysis using a wider feature space, possibly with more recording channels. Furthermore, we realized that some volunteers performed better in terms of classification results. Although this difference might be caused by some recording problems such as noise, electrode connection problems or concentration level, training data amount is also significant. Since the performance deteriorates in the nail environment and also depends on the subject, the useful data coming from nail sub-sessions may not be sufficient to train a comprehensive model. Therefore, enhancing the data recording process would probably result in higher accuracies.

Another future work direction would be to increase the number of classes and classify three different speed levels. The addition of an intermediate speed level would make the problem more challenging. Thereby, intention level of patients under rehabilitation process may be detectable at three levels and the difficulty of their daily schedule may be updated according to their motivation. Moreover, since the classes are linked with executed tasks, it is possible to collect and analyze surface Electromyogram (sEMG) data of subjects. Such data can be used to remove any EMG artifacts in the EEG data as well [17].

V. Conclusion

In the present study, classification of motor task execution velocity from EEG data is considered and a setup is designed to collect data for such a classification task. Distinctions of this setup are its horizontal structure which prevents fatigue and resemblance to real-world tasks. Eight participants performed a right arm movement task at two speed levels, not strictly set, but implied by the experimental scenario. Results show that motor task execution speed level is distinguishable using EEG signals with above chance-level accuracies.

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