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CLASSIFICATION OF VARIOUS GRASPING TASKS BASED ON TEMPORAL SEGMENTATION METHOD USING EEG AND EMG SIGNALS

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ABSTRACT: Electroencephalography (EEG)-based brain-computer interface (BCI) system is useful for rehabilitation and external device control. In this study, we analyzed the decoding of five different grasping tasks in actual movement and motor imagery (MI) paradigms. Eight healthy subjects participated in this experiment. They executed and imagined five sustained grasping tasks. In this actual movement and MI experiment, we proposed a muscle-related temporal segmentation method by detecting the electromyograph (EMG) signals. At the same time, we used common spatial patterns (CSP) and the regularized linear discriminant analysis (RLDA) for the EEG analysis. As a result, we classified the five different grasping tasks in the offline experiment and obtained average classification accuracies of 60.85$\pm$7.71% for actual movement and 37.95$\pm$7.86% for MI, respectively. This result is encouraging, and the proposed method could potentially be used in future applications, such as a BCI-driven robot hand control for handling various daily use objects such as cup, ball, pencil, bolt, and card.

INTRODUCTION

Brain-computer interfaces (BCIs) are promising tools for detecting user intention and controlling robotic devices such as upper limb prosthesis [1]. Many research groups use electroencephalography (EEG) based BCI because of its cost-effectiveness and convenience. The EEG signals which are generated by brain activities can be separated from different paradigms or physiological phenomena such as visually evoked potentials, slow cortical potentials, and sensorimotor rhythms. In particular, sensorimotor rhythms include two kinds of amplitude modulations known as event-related desynchronization (ERD) and event-related synchronization (ERS) that are generated by sensory stimulation, motor behavior, and mental imagery [2, 3]. ERD and ERS are often used in such movement-related BCI studies and detected in the mu band [8-13] Hz. In this study, we used common spatial patterns (CSP) to avoid using the mu band only and extracted features from the extended frequency bands. The CSP method shows clear patterns and spatial features of brain activities so that it is effective in classifying motor imagery (MI) and actual movement [3].

Three related kinds of research inspired our study. Schwarz et al. [4] tried to decode natural reach and grasp actions from human EEG. They attempted to identify three different executed reach and grasp actions, namely lateral, pincer, and palmar grasp, utilizing EEG neural correlates. Throughout the experiment, they achieved binary classification accuracies of 74.2% between grasp types and 65.9% for the multi-class grasp types classification at the offline actual movement experiment. In the other case, Ofner et al. [7] had encoded single upper limb movements in the time-domain of low-frequency EEG signals. The primary goal of the experiment was to classify six different movements, and those are elbow flexion, extension, hand grasp, spread, wrist twist left, and twist right. They achieved the final classification accuracies of 55% in actual movement and 27% in MI.

Agashe et al. [8] had decoded hand motions with a different approach. They demonstrated that global cortical activity predicts the shape of the hand during grasping. It was an offline study, and they inferred from EEG hand joint angular velocities as well as synergistic trajectories as subjects perform natural reach-to-grasp movements. Classification accuracy between the predicted and the actual movement kinematics was 49%. They showed real-time closed-loop neuro-prosthetic control of grasping by an amputee and the feasibility of decoding brain signals of a variety of hand motions. However, these three related studies could not achieve robust decoding performance in MI paradigm due to its complex characteristic of the brain signal data. We tried to solve the problem with a new approach and perspective.

In this paper, we present the classification of grasping tasks within EEG signals for non-invasive BCI. The objective of this study is to confirm whether the method of muscle-related temporal segment selection by detecting the change of signals from each electromyograph (EMG) channel improves the BCI performance of each subject or not. At the same time, we proved the feasibility of classifying various grasping tasks in the right hand from EEG signals with the proposed method in the MI paradigm. The EEG signals from different participants were acquired, and we only selected muscle-related temporal segments from a whole-time domain. With the running of sufficient experiment trials and data analyses, we were able to construct a robust decoding model using our proposed

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Figure 1: Description of the five grasping tasks and the experimental setup. (**left**) Five different reach-and-grasp tasks and the starting position. Five different grasping actions are matching to specific objects. (**right**) Experimental environment for EEG and EMG signals acquisition.

method to classify five different grasping tasks, which can be contributed to developing a robot hand control system driven by EEG signals and based on MI in the future.

MATERIALS AND METHODS

Participants: Eight healthy subjects with no history of neurological disease were recruited for the experiment (right-handed males aged 24-33 years). At the same time, we purposely chose every subject who already experienced the BCI experiment in order to maintain the stability of EEG and EMG signals as musch as possible. For the best results and to verify the feasibility of decoding complex grasping tasks, we only acquired data from trained subjects.
This study was reviewed and approved by the International Review Board, at Korea University [1040548-KU-IRB-17-172-A-2], and written informed consent was obtained from all participants before the experiements.

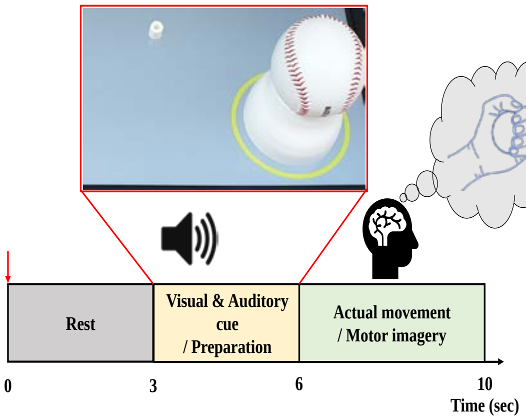

Figure 2: Illustration of experimental protocol to decode five class reach-and-grasp actions in actual movements and motor imagery paradigm.

Experimental Setup: During a session of the experimental protocol, the subjects sat in front of a 32-inch LCD monitor screen, in a comfortable chair. The screen was installed horizontally on the table to make subjects can see the objects and visual cue (flashing yellow circle around the targeted object) without moving their head. Figure 1 indicates the experimental setup and the environment during the entire session. The subjects were asked to perform or imagine a specific grasping task following each auditory and visual cue. The subject imitated the designated grasping tasks, including a half-opened hand shape that indicates muscle relaxation during the rest period (in the starting position). During the experiment, the subjects were asked to perform five different grasping tasks, which are illustrated in Figure 1.

Data Acquisition: EEG and EMG signals were collected using maximum possible channels for data collection for future analysis. During the experiment, the EEG data were collected at 1000 Hz using 64 Ag/AgCl electrodes in 10/20 international system via BrainAmp (BrainProduct GmbH). At the same time, a 50 Hz notch filter was used to remove power frequency interference. The FCz and FPz were used as reference and ground electrodes, respectively. All impedances were maintained below 10 kΩ. From the entire 64 EEG channels, only 20 channels (FC5, FC3, FC1, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, and CP5) were used for data processing, because we expected to suppress the artefacts such as signals from eye movements by removing peripheral channels except on the motor cortex. The 20 channels were located only on the motor cortex to make sure that the recorded EEG signals are highly related to the motor-related potentials, which are from the actual movement and MI, as shown in Figure 3.
In the case of EMG data acquisition, we used 5 Ag/AgCl electrodes (CH1: extensor pollicis brevis, CH2: extensor digitorum, CH3: flexor digitorum profundus, CH4: flexor digitorum superficialis, CH5: reference) from the same equipment during EEG data recording. The EMG channels were attached on the right arm to detect signal

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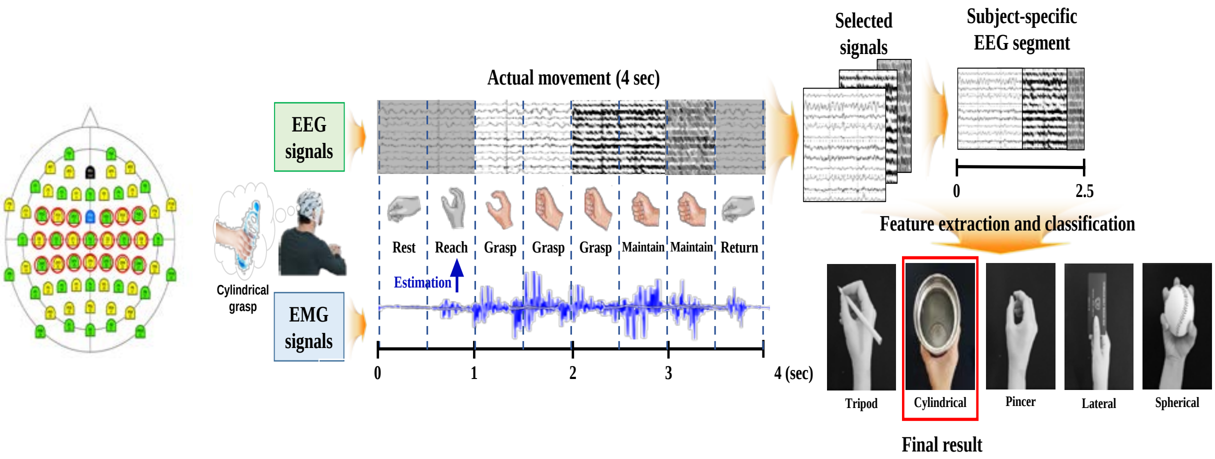

Figure 3: (**left**) EEG location of selected 20 channels that minimize the artefacts. (**right**) Proposed method to select subject-specific time segments during the classification. Measuring EMG signals to find the optimized time segments for feature selection on a trial. Select a specific 2.5-second length of time segment from 0 to 4s total length of a single trial.

change while the subject performed grasping tasks [7]. The one channel on extensor digitorum (CH2) was selected, and the EMG signals were first processed by 50 Hz notch and filtered by a 5-500 Hz band-pass filter [8, 9].

Every subject performed 75 trials per each grasping task (375 trials: 5 classes x 75 trials). They were also asked to perform or imagine a specific grasping task once but not repetitively in the actual movement/motor imagery period of 4 sec, shown in Figure 2.

Data Analysis: Filtering the EEG signals was a significant process in the experiment. We grouped the three most used motor-related EEG bands mu [8-13], beta [13-30], and delta [0.1-3] in Hz using a 2nd order of Butterworth filter [5, 10] and tested for the best performance. In particular, we chose [0.1-3] Hz to decode our EEG data because it showed the best classification result compared to using the other bands in this experiment. EMG signals were analyzed to detect muscle-related temporal segments by measuring the activation of muscles when the subject performed the actual movement. We calculated the mean integrated EMG (IEMG) as the indicator of the muscle activity during each grasping task. IEMG is capable of reflecting the contraction property of muslces [8-10].

It is defined as:

$$IEMG = \Sigma_{i=1}^{n} |x_i| \tag{1}$$

Here, x_i represents the ith sample of EMG signal and n represents the length of time segment.

We separated one trial of 4 seconds in eight (0.5 seconds for each segment) and selected only muscle activation point when performing grasp. We excluded the segmented EEG signals when the proposed model

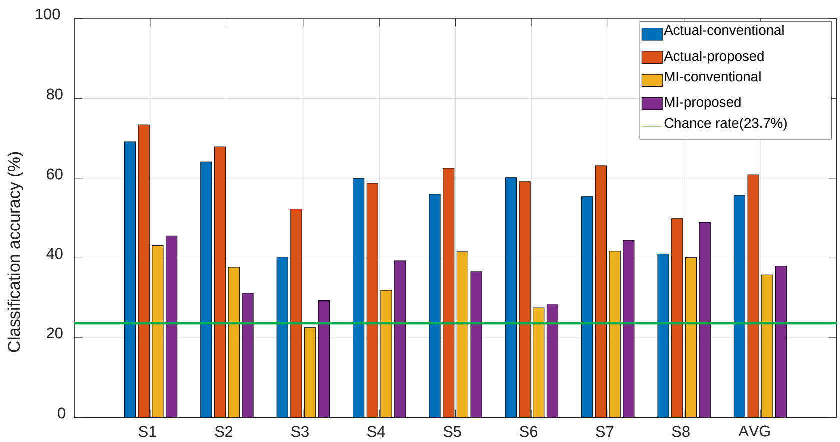

Figure 4: Classification accuracies for decoding 5-class grasping tasks in [0.1-3] Hz. Average MI decoding accuracy was 37.95% and average actual movement accuracy was 60.85%, respectively. 10 by 10 cross-validation was applied.
***Conventional: using fixed 4-second temporal segmentation to extract CSP features**
***Proposed : using subject-specific temporal segmentation of 2.5-second based on muscle-related signals**

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Table 1: Classification accuracies of 5-class grasping task according to motor-related frequency bands

	Actual movement (Cylindrical / Spherical / Pincer / Tripod / Lateral)			**Movement imagery** (Cylindrical / Spherical / Pincer / Tripod / Lateral)		
	[0.1-3] Hz	**[8-13] Hz**	**[13-30] Hz**	**[0.1-3] Hz**	**[8-13] Hz**	**[13-30] Hz**
Sub 1	**73.38 %**	65.80 %	57.70 %	**45.52 %**	41.25 %	43.55 %
Sub 2	**67.87 %**	33.60 %	41.40 %	31.17 %	**36.01 %**	27.53 %
Sub 3	**52.27 %**	37.93 %	43.80 %	**29.33 %**	24.75 %	28.65 %
Sub 4	**58.73 %**	45.60 %	38.75 %	**39.30 %**	25.25 %	33.82 %
Sub 5	**62.50 %**	53.73 %	45.58 %	36.55 %	**37.09 %**	55.48 %
Sub 6	59.12%	**69.06%**	57.40%	**28.45%**	22.54%	21.99%
Sub 7	**63.12%**	51.43%	58.32%	**44.39%**	30.03%	29.32%
Sub 8	**49.85%**	43.44%	35.93%	**48.90%**	34.94%	44.33%
Avg.	**60.85 %**	50.07 %	47.36 %	**37.95 %**	31.48 %	35.58 %

estimates the stages are in progress of rest, reach, and return. This temporal segment indicates when the subjects actually move their hand to grasp the designated object. These temporal segments are subject specific so that if a subject has the temporal segment in between 1 second to 3.5 seconds (2.5-second length), we can apply this segment to analyze training and test data. However, we need to find differernt temporal segments for the other subjects.
After selecting these temporal segments, we applied the segment to cut the original EEG data in limited length so that eventually we could pick the data at the movement-related time point. Common spatial patterns (CSP) and regularized linear discriminant analysis **(**RLDA) were applied for further feature extraction and classification.

Of course, we could not measure any distinguishing characteristic in EMG data during the MI paradigm [10, 11]. However, applying the trained temporal segment using the data from the actual movement experiment was effective to most of our subjects when classifying MI.

RESULTS

Through the experiment, we confirmed the feasibility of classifying five different grasping tasks in the right hand. Figure 4 presents the classification accuracy results in actual movement and MI with bar graphs. In the actual movement session, in the red bars of Figure 4, every subject excluding S4 ans S6 showed increasing trends of accuracies approximately 3 to 12% compared to the conventional method. Classification accuracies of S3 and

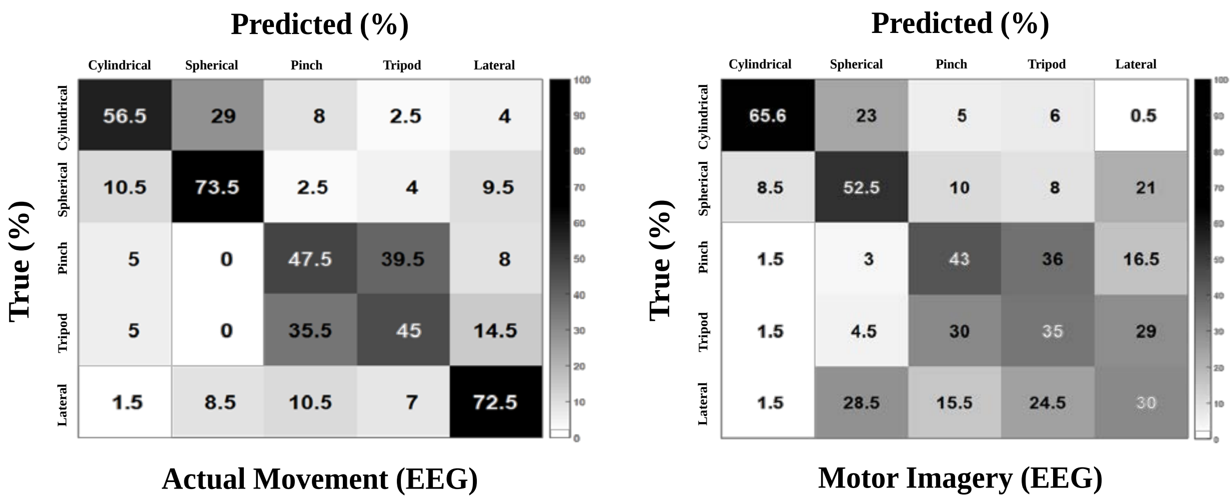

Figure 5: Confusion matrices of (**left**) actual movement classification and (**right**) MI classification results. Showing significant differences among each class especially on the power grasping tasks (cylindrical and spherical) and precision grasping tasks (pinch, tripod and lateral). The classification result of MI shows a similar tendency to the result from the movement.

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S7 when using 2.5-second length of time segmentation were dramatically improved and finally peaked at 63.12% while the other subjects showed little increase compared to the conventional method. On the other hand, during the MI session, the classification accuracies continuously increased, while some of the subjects showed a decrease. Most of them reached the higher classification accuracies when we applied our proposed decoding method. In the case of the S2 and S5, the classification accuracy started to decrease, but the subjects showed little decrease, while the other subjects showed a more significant increase in accuracy. For example, S4 and S8 achieved dramatic improvements of 7.42% and 8.81%, respectively.

According to the results, each subject showed the highest actual movement or MI performance at a different point in time, but most of them showed increase in performance with applying muscle-related temporal segment selection method.

The different results in five class multi-classification accuracies between actual movement and MI are strongly affected by the muscle-related time segment selections. For some subjects, such as S4 and S8, more improvement was shown in the classification accuracy when adopting the proposed method that was trained with actual movement data and applied in the MI paradigm than when using the same method with the actual movement paradigm. For instance, during the MI classification, the average accuracies of the proposed method increased by almost 2 to 9%. These were higher than the accuracies of the conventional model, using an ordinary fixed 4-second temporal segment.

Table 1 presents entire classification results of all subjects in three different motor-related frequency bands. First, we analyzed classification accuracies in delta band [0.1-3] Hz. Several related researches already showed the feasibility of decoding upper limb or hand movements in low frequency EEG [4, 5]. In the delta band most of subjects showed the best classification accuracy compared to the other bands. Traditionally the beta and mu bands are widely used to decode actual movement and MI from EEG signals. The classification results in the both two motor-related frequency bands are similar. Some of subjects showed the best results at the [8-13] or [13-30] Hz but most of them are performed the best in low frequency.

DISCUSSION

In this study, we confirmed the effectiveness of using our proposed muscle-related temporal segment selection to improve classification accuracy in both of actual movement and MI paradigms. As we can see in Figure 4, the results showed the feasibility of the proposed method as a temporal segment selection strategy feature to increase multi-class classification accuracy on set purpose, especially in actual movement paradigm. Although the visual cue-based synchronous system executed the experiment in an offline scenario, the subjects completed MI with different speed, trajectory, and force. We could see that the muslce-related temporal segment selection is working and adaptive in the MI paradigm even though it was trained with actual movement data. We suppose it is because the subjects imagine in a similar way and rhythm to actual movement. During each of the trials, the subjects only used intuitive motor imagery when they were asked to perform the specific grasping task. Hence, selecting the muscle-related temporal segment length to extract the apparent movement-related EEG features at the exact time interval for each particular individual during MI paradigm is useful when the situation in which the subjects perform is unobservable and there are variable motor-related brain activities.

CONCLUSION

Classifying five different grasping tasks from EEG signals within a hand is very challenging, but fortunately, we confirmed the feasibility. The results showed improvements to the overall classification accuracies with our proposed method. In the future work, we will focus on increases in reliability and efficiency to develop a robust MI decoding method based on muscle-related signal data with advanced machine learning and deep learning approaches. We will also modify our offline experimental protocol to be asynchronous and online-oriented for the development of practical BCI based robot hand control.

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