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DECODING OF WALKING INTENTION UNDER LOWER LIMB EXOSKELETON ENVIRONMENT USING MRCP FEATURE

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ABSTRACT: In brain-machine interface (BMI) researches, a fast and accurate detection of user intention is an important research issue for an efficient human-machine interaction. Among electroencephalography (EEG)-based BMI paradigms, a movement-related cortical potential (MRCP) could be useful to recognize user intention due to its characteristics of spontaneity and low latency. Therefore, in our study, we propose a MRCP feature selection method for decoding user intention under the powered exoskeleton environment. We combined two spectral features that were extracted from readiness potential (RP) and movement-monitoring potential (MMP) sections, respectively. In each MRCP section, we estimated optimal frequency bands for the discriminative feature using a nested cross-validation. Five healthy subjects who were wearing the exoskeleton performed a self-initiated walking task. Our results showed the grand averaged classification accuracy of 87.6%. To our best knowledge, we first validated a single-trial analysis using the MRCP data acquired from self-initiated exoskeleton walking. Our experimental results present that the proposed MRCP-based exoskeleton control system is becoming more feasible for real-world applications.

INTRODUCTION

Brain-machine interface (BMI) is a communication system between users and machines, in which users can control the external devices through conveying user's intention without direct manipulation or the activations of peripheral nerve system [1]. The BMI techniques have commonly used electroencephalography (EEG) signals to recognize user intention for controlling external devices such as wheelchairs, robot arms, or robotic exoskeleton [2, 3]. Recently, EEG-based BMI has been developed for not only healthy people but also the patients with paralysis or nerve damage in neuro-rehabilitation [4].

Movement-related cortical potential (MRCP) is one of the representative slow cortical potential (SCP) components, which is measured by a slow decrease in the EEG amplitude over primary motor cortex (M1) during a motor task in human. Also, it is a spontaneous potential which is generated by execution or imagination of either cue-based movement paradigm known as a contingent negative variation (CNV) or self-paced movement paradigm. MRCP comprises two main components that are readiness potential (RP) and movement-monitoring potential (MMP). RP is a negative cortical potential which has two fundamental parts before the movement onset. Negative slope, called 'early bereitschaftspotential (BP)', begins about ($1 \sim 2$)s before voluntary movement onset. About 1s before the movement onset, steeper negative slope is called 'late BP' or 'motor potential (MP)' (Fig. 1). In contrast, MMP is a positive cortical potential which reflected an outcome of the motor process. After the movement onset, the MMP generated as an increase deflection for returning to initiate state (Fig. 1). MRCP reflects the stepwise process of movement preparation/planning and execution [5]. It could be a useful feature for an intuitive assistive robot control due to its advantages of spontaneous potential and early detection of user intention based on a single-trial. MRCP researches have been investigated to amyotrophic lateral sclerosis (ALS), stroke, and paralysis patients for rehabilitation with assistive robots as well as to the normal person for controlling BMI-based external devices [6].

Therefore, the researchers in previous studies decoded user's movement intention from MRCP in the various experiment paradigm (e.g. self-paced arm movement (reaching task) [7], executed and imagined foot movement (foot dorsiflexion) [8], self-initiated walking [9]). They have applied MRCP decoding system to BMI-based rehabilitation for inducing patient's brain plasticity effectively. These studies have utilized different EEG data acquisition techniques with different electrode montage, brain signal enhancement technologies, and some of them presented an usefulness of EEG data acquired in the real-time BCI. They verified that their approaches could be useful for accurate detection or classification of user intention from MRCP. Also, various machine learning approaches were applied for a single-trial MRCP analysis [10, 11].

However, MRCP-based BMI systems have a low performance to recognize movement intention in the single-trial basis. The system performance to detect user intention still requires more stable accuracy for efficient and reliable BMI system. Also, the current MRCP-based detection systems are difficult to apply in asynchronous BMI system. Because the MRCP is primarily extracted from the narrow frequency ranges (i.e. the SCP ([0.1-1] Hz and delta ([1-4] Hz) band, etc.) for all subjects.

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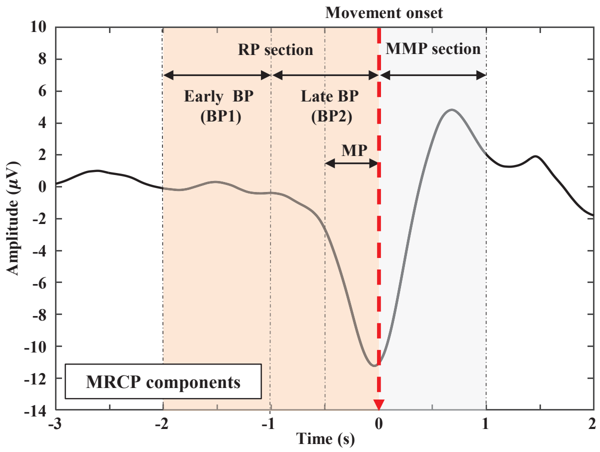

Figure 1: Representation of MRCP amplitude fluctuation at Cz electrode. Movement onset is defined at the time point 0s. The MRCP comprises RP and MMP sections. (In RP section, (-2 ∼ -1)s is early BP, (-1 ∼ 0)s is late BP, (-0.5 ∼ 0)s is motor potential (MP), and after movement onset, (0 ∼ 1)s is MMP section).

For these reasons, we hypothesized that the MRCP detection performance would be improved using the subject-dependent MRCP feature selection method. We approached in two main perspectives. In spectral-domain perspective, we extracted the optimal frequency band by nested cross-validation based on classification accuracy across each filter bank. In temporal-domain perspective, we approached that motor-cortical fluctuations in EEG have different frequency power in the pre-movement state (RP section) and after the movement onset (MMP section) during the MRCP evoked time. We also designed an exoskeleton control system for acquiring the MRCP data under the real-world exoskeleton environment. Hence, we propose a subject-dependent MRCP feature selection method for the accurate detection of user intention on the single-trial basis.

MATERIALS AND METHODS

A. Experimental protocols: Fig. 2 shows our designed experiment system for acquiring MRCP data under a lower limb exoskeleton walking environment.

First, we used the lower limb exoskeleton (REX, Rex Bionics Ltd) module. The exoskeleton has various functions; self-balancing, self-supporting, and programmed motions (e.g. walking, turning, sitting, standing, and shuffling). It allows a person to move by joystick or wireless interface [12]. In our experiment, the exoskeleton was controlled by electromyogram (EMG) signal which generated from muscle movements. We used a wireless EEG and EMG module (MOVE, BrainProduct GmbH). The EEG and EMG signals were transmitted to the recording program (BrainVision Recorder, BrainProduct GmbH) simultaneously. The signal amplifier was located on the right arm of the exoskeleton. The EEG module was used for decoding the user's walking intention from MRCP. The EMG module was used for acquiring the electrical signals by muscle movements from the right leg. The EMG module detected the movement onset triggers that generated when the EMG activity exceeded a pre-defined threshold value.

Five healthy subjects without any neurological or physical disorder history participated in the experiments (aged 26-29, five males). The EEG data were acquired using 32 Ag/AgCl electrodes (Fp1, Fz, F3, F7, C1, FC5, FC1, C3, T7, CPz, CP5, CP1, Pz, P3, P7, O1, Oz, O2, P4, P8, CP6, CP2, Cz, C4, T8, C2, FC6, FC2, F4, F8, Fp2, and POz) following 10/20 international systems. The ground electrode was mounted on FPz and reference electrodes

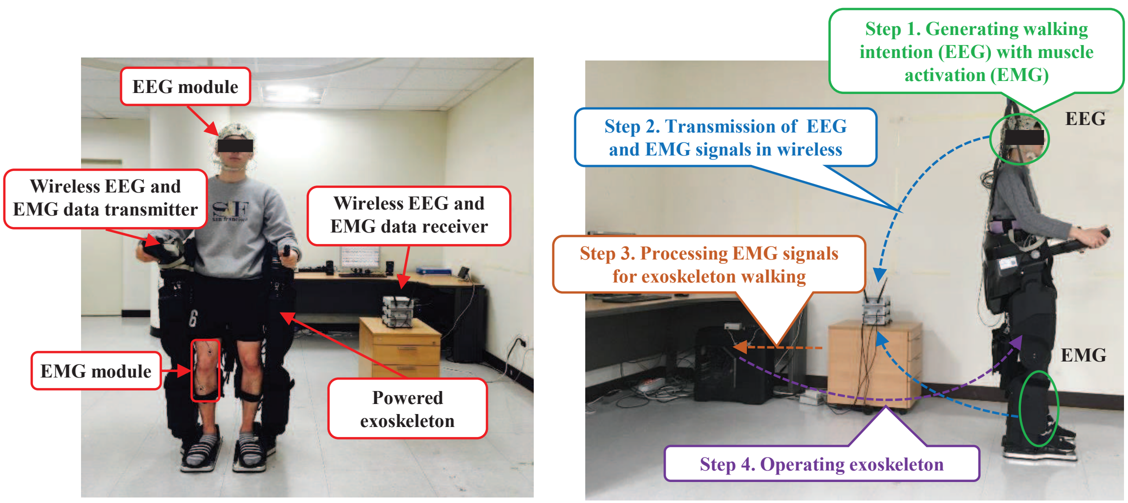

Figure 2: Experimental modules (left) and protocols (right) for MRCP data acquisition under lower limb exoskeleton environment. The subjects performed the self-initiated exoskeleton walking task during the experiment. The exoskeleton is controlled by the EMG activation.

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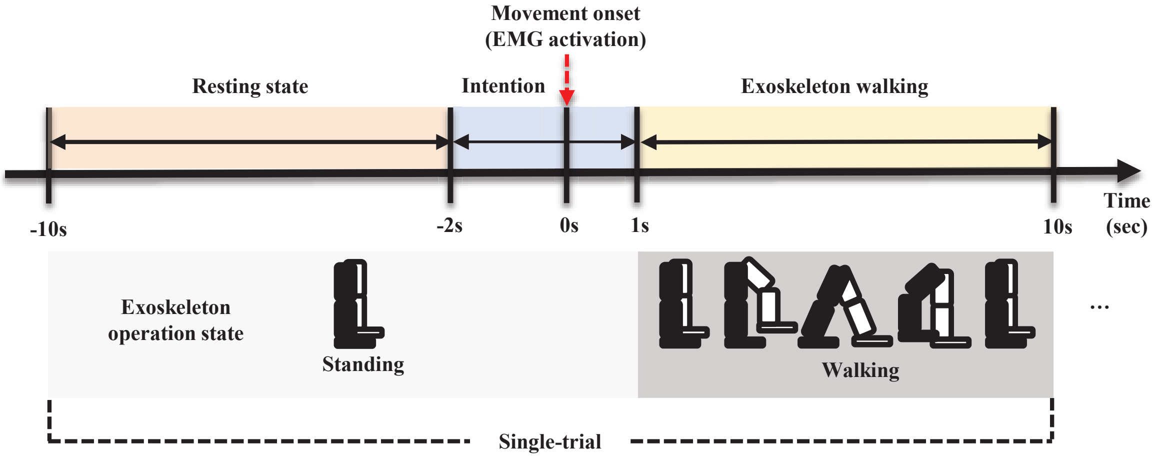

Figure 3: Experimental paradigm. After the experiment starts, the subjects performed self-initiated walking whenever they intended to walk in 50 trials. The lower limb exoskeleton is operated walking task for 8s (movement onset triggers were marked). After one-step exoskeleton walking, the resting state was given for 8s (the resting triggers were marked).

on FCz. All impedance of electrodes were maintained below 10kΩ. The sampling frequency rate was 1000Hz. A notch filter frequency rate was 60Hz for reducing DC power supply noise.

The EMG data were recorded using two bipolar Ag/AgCl electrodes on the tibialis anterior (TA) and biceps femoris (BF) muscles of the right leg. These muscles were selected because of fast muscle activation in walking [8]. The EMG data were preprocessed using 2s sliding window size with a 100ms shift. The data filtered by a zero-phase Butterworth fourth-order band-pass filter at [0.05-60] Hz and were rectified using the absolute value of filtered EMG data and calculated the moving average of the EMG amplitudes window size in an online manner.

B. Experimental paradigm: In exoskeleton walking task, the subjects performed the self-initiated exoskeleton walking when they intended to walk. The lower limb exoskeleton was operated by the movement onset trigger which was generated by EMG activation. (Note that the experiments were conducted by self-paced walking, not a cue-based instruction) The exoskeleton operated for 9s as one-step walking. After one step had been performed, the resting state was given to the subject for 10s. The subjects were asked to relax the muscle because the muscle tension could affect contamination of EMG signal. This experiment process is a single-trial of the entire experiment paradigm. The subjects performed the self-paced exoskeleton walking over 50 trials (Fig. 3).

C. Data processing: The acquired EEG and EMG data were processed using a BBCI toolbox [13]. First, we composed the frequency filter bank for extracting subject-dependent optimal frequency band. The frequency filter bank was comprised by thirty different frequency bands such as [0.05-1,2, ...10] Hz, [0.1-1,2, ...10] Hz, and [0.5-1,2, ...10] Hz. The EEG data were randomly selected 80% of the trials as training set and use remaining 20% as test set for applying the principle of nested cross-validation to design the framework of signal processing (Fig. 4). In the inner loop (blue line), we selected subject-dependent optimal frequency bands based on the MRCP classification accuracies using training set, which is band-pass filtered using the frequency filter bank according to each RP and MMP section. After the inner loop step, the selected frequency bands were updated as band pass filter parameter for the outer loop (red dashed line). In the outer loop, the MRCP detection performance was calculated using selected subject-dependent frequency band with test set.

More in detail, in the inner loop, the acquired EEG data were pre-processed by 2nd Butterworth band-pass filter according to each frequency band at the filter bank and down-sampled from 1000Hz to 100Hz. The filtered data were then spatially filtered using large Laplacian filter to maximize spatial distribution for the poor spatial resolution [15]. The large Laplacian filter was applied at C1, C2, CPz, and Cz channels, respectively, using the surrogate 8 channels. We did not apply the artifact rejection techniques because the subject who wearing the exoskeleton maintained the standing state only (Fig. 3). The spatially filtered data were segmented from (-6 ∼ 4)s by the movement onset. The epoched data were divided into RP section (-2 ∼ 0)s and MMP section (0 ∼ 1)s respectively (Fig. 1). The data of RP and MMP sections were defined as "walking intention state" class. The data in the interval of (-5 ∼ -2)s were defined as "resting state" class. Each class consisted of the data which is filtered by each frequency band. Especially, in the resting state, we also divided the epoched data as (-5 ∼ -3)s and (-3 ∼ -2)s. The data for each interval applied the same frequency band used for filtering the RP and MMP section, respectively.

Before the extracted the RP and MMP features, the epoched data were computed the correlation coefficient signed r-square values between walking intention and

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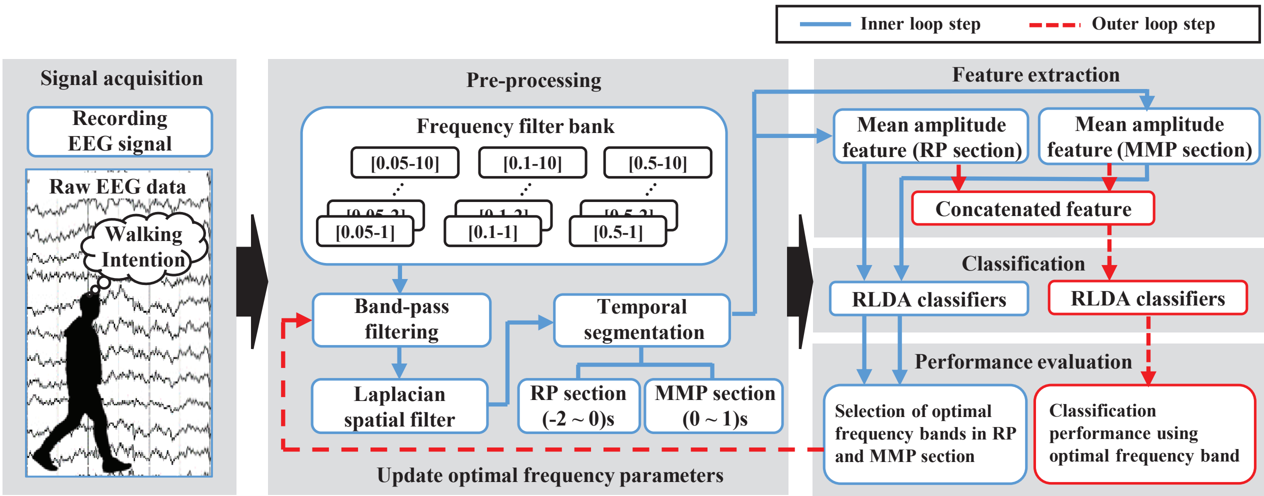

Figure 4: The flowchart of the subject-dependent MRCP feature selection for decoding of walking intention

resting state classes for detecting statistically significant time intervals for each channel. In the RP section, the signed r square values showed relatively high values between walking intention and resting state at Cz, C1, C2, and CPz channels. In the MMP section, the signed r square values showed relatively high values at Cz, C1, C2, FC1, and FC2 channels (Fig. 5). Specifically, the signed r square value showed significant discriminant values between classes at Cz, C1, C2, CPz, CP1, CP2 channels nearby motor cortex compared to other channels. Therefore, Cz, C1, C2, and CPz channels were selected for extracting MRCP features.

For extracting MRCP feature, we extracted mean amplitude feature in the 0.2s intervals at all classes (walking intention and resting state) from epoched data.

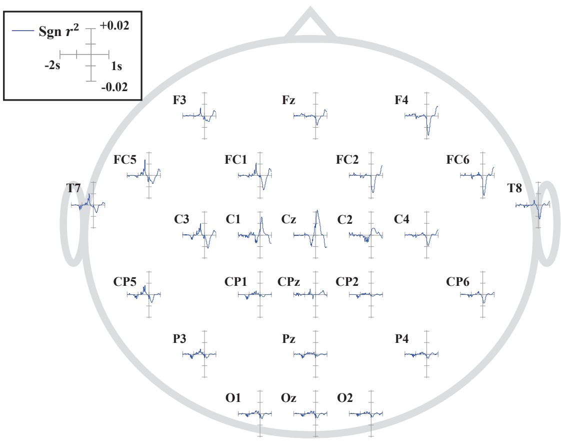

Figure 5: Topographic plots of signed r-square values between walking intention and resting state classes at subject E. The signed r-square represented the relatively discriminant degree between classes in each channel.

The extracted features composed 15 $\times$ 4 matrix (feature vector $\times$ channel). The features were classified as walking intention and resting state classes using regularized linear discriminant analysis (RLDA). The RLDA is one of the methods to simple classification modeled with normal distribution in each class samples. In our data processing, the RLDA was used as a classifier to detect walking intention depending on each frequency band. 10-fold cross validation was applied for evaluating of MRCP detection performance.

Therefore, through the inner loop, we obtained thirty MRCP classification accuracies using the frequency filter bank depending on RP and MMP section, respectively. The subject-dependent optimal frequency bands were selected to have the best classification accuracy at each RP and MMP section.

In the outer loop, the selected frequency bands for each section were updated to band-pass filter parameter in the pre-processing step. The raw EEG data were band-pass filtered using the updated frequency bands.The EEG data processing step of the outer loop is processed the same way as in the inner loop (i.e. down-sampled frequency rate 1000 Hz to 100 Hz, applying large Laplacian spatial filter, channel selection, time segmentation, extraction of mean amplitude feature). The processed RP and MMP features were concatenated for comprising either walking intention class or resting class. Finally, the RLDA classifier was used as detection of user's walking intention from subject-dependent MRCP feature. The MRCP detection performance was evaluated using test set.

Through the proposed method, we obtained the subject-dependent frequency parameter for robust MRCP detection system.

RESULTS

Tab. 1 shows the selected frequency bands in each RP and MMP section across subjects and the results of MRCP classification accuracy based on a single-trial analysis. The grand average classification accuracy is 87.61% across five subjects. Through this results, we observed that the frequency bands were extracted discrimi-

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natively for each RP and MMP section. Also, the optimal frequency bands were different in each subject.
Fig. 6 shows the significant MRCP patterns which were observed in self-initiated exoskeleton walking task. The actual movement onset (0s) were set when the EMG signals exceeded pre-defined threshold amplitude. The averaged MRCP patterns are indicated from (-2 ∼ 1)s at Cz electrode in subject C and E. The MRCP were baseline corrected from (-2 ∼ -1.5)s by the movement onset time. The black line indicates the MRCP patterns filtered by the selected frequency bands in subject C and E. In subject C, the MRCP features were filtered by [0.1-1] Hz and [0.05-9] Hz across RP and MMP section, respectively. Also, in subject E, the MRCP features were filtered by [0.1-10] Hz and [0.5-2] Hz across sections. The steeper negative slope indicates from (-1 ∼ 0)s (RP section) and, after movement onset, the positive slope indicates from (0 ∼ 1)s (MMP section).

Table 1: Selected frequency bands and classification accuracies of MRCP for each subject

Subject	Selected frequency band [Hz]		Performance (%)
	RP section	MMP section	
Sub A	[0.5-10]	[0.1-7]	94.12
Sub B	[0.5-4]	[0.5-2]	75.22
Sub C	[0.1-1]	[0.05-9]	85.29
Sub D	[0.5-3]	[0.5-9]	86.36
Sub E	[0.1-10]	[0.5-2]	97.06
Average			87.61 ± 8.5

Scalp topographies are plotted to show the spatial distribution of MRCP patterns (Fig. 6). The time interval separated into three sections to observe the specific time-spatial changes of MRCP patterns. As we mentioned (Fig. 1), the time interval of (-2 ∼ -1)s is 'early BP' in the RP section, (-1 ∼ 0)s is 'late BP' in RP section. (0 ∼ 1)s is MMP section. Scalp topographies in the RP section (-2 ∼ 0)s appeared gradually negative distribution in the central and post-central area. Especially, in the range of (-1 ∼ 0)s, the scalp topography shows significant the negative distribution relatively nearby motor cortex in Cz, CPz, C1, and C2 channels. After the movement onset in MMP sections (0 ∼ 1)s, the intensity of the spatial distribution was observed returning from negative to initial distribution.
Therefore, we confirmed that the scalp topography in 'late BP' section shows the relatively more negative spatial distribution compared to 'early BP' section. Also, scalp topographies in MMP section shows certainly positive spatial distribution.

DISCUSSION

In this paper, we propose a subject-dependent MRCP feature selection method for robust detection of user's walking intention on the single-trial basis. Also, we designed a single-trial MRCP acquisition system under the lower limb exoskeleton environment. Due to our designed system, we could obtain the EEG signals with respect to walking intention from MRCP feature with the self-initiated exoskeleton walking.
Through the proposed method, we have observed that movement intention can be decoded above chance level using optimal frequency bands for each subject compared to different EEG frequency bands (i.e. SCP, delta bands, etc.).
Regarding system performance, we used a systematic ap-

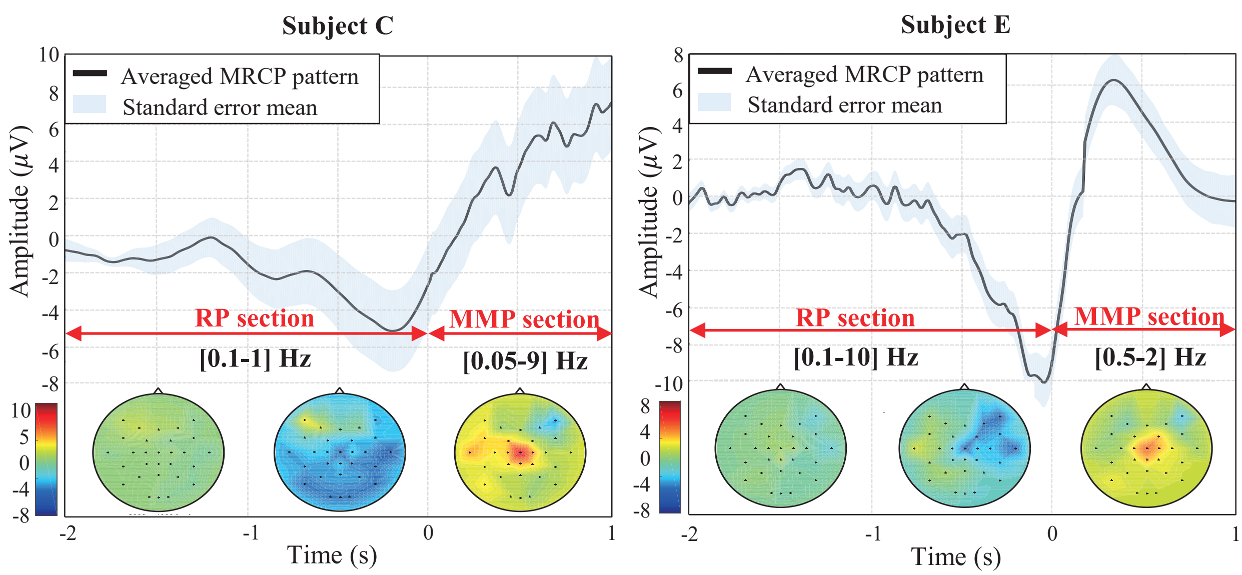

Figure 6: Time-amplitude representation of averaged MRCP filtered by selected frequency bands at channel Cz in subject C and E. Representation of scalp topographies from MRCP using selected frequency bands in each section.

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proach for detecting the onset of self-initiated exoskeleton walking to extract user's walking intention. Outcome of the proposed method showed that subject-dependent EEG features are also important to detect the movement intention from MRCP. Also, we validated that subject-dependent optimal frequency parameter could improve the performance of MRCP detection system compared to the heuristic frequency bands.
Our current study, however, focused on applying to stroke patients or lower limb discomfort people who are able to extract EMG signal for the real world application control or gait rehabilitation. Hence, we have developed our system can be applied in the online environment without EMG. We have implemented a 3s sliding window which can filter in real-time with an optimal RP frequency band of 2s and an optimal MMP frequency band of 1s.

CONCLUSION

In the context of BMI-based real world application control or gait rehabilitation, the robust detection of movement intention is an essential and critical issue for the development of self-initiated BMI control systems. Fast and accurate detection of self-initiated movement intention using MRCP has raised hope for rehabilitation scenarios in which neural plasticity and brain function recovery implicitly.
In our study, we proposed the subject-dependent MRCP feature selection method for robust MRCP detection based on a single-trial. The result showed that grand-averaged classification accuracy is 87.6 $\pm$ 8% using the single-trial MRCP data acquired from the self-initiated exoskeleton walking task in the ambulatory environment. In our method, the temporal intervals of MRCP are divided into two sections of RP (-2 $\sim$ 0)s and MMP (0 $\sim$ 1)s. The optimal frequency band has validated from each temporal interval independently. We firstly report that the RP and MMP component have different optimal frequency ranges, and it highly depends on the individual subject. Our data were acquired by healthy subjects whose wearing the lower limb exoskeleton.
Our study still needs to demonstrate the possibility of applying to the stroke patients or the lower limb discomfort people for the online system. Hence, future work will target to devote the robustness of our method with those people, and prove the possibility of MRCP-based exoskeleton system as a real-world application.

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