Detection of lower-limb movement intention from EEG signals

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***Abstract*—Brain-computer interfaces (BCIs) have been investigated in recent years to transfer the brain activities to external devices as rehabilitation tools in clinical trials. Here we present a BCI to detect lower-limb movement intention from electroencephalography (EEG) signals, combining movement-related cortical potentials (MRCPs) and sensorymotor rhythms (SMRs) with support vector machine (SVM) classification model. We report analysis of the EEG correlates of five healthy subjects while they perform self-paced ankle dorsiflexion. The average detection accuracy was 0.89 $\pm$ 0.04, while the latency was -0.325 $\pm$ 0.127 ms with respect to actual movement onset. The combination of these two features has shown significantly better performance ($p < 0.01$) than the models using either MRCP or SMR. It is also demonstrated that complementary information was employed to boost the detection performance. The proposed paradigm could be further implemented as a brain switch in neurorehabilitation scenarios.**

***Index Terms*—Brain-computer interface (BCI), electroencephalography (EEG), movement-related cortical potential (MRCP), sensorymotor rhythm (SMR)**

I. Introduction

In the past few decades, brain-computer interfaces (BCIs) have emerged as new approaches for communication and control, bypassing the normal physiological neural pathways [1]. They have been treated as rehabilitation techniques, especially for severely disabled subjects, e.g., completely locked-in patients caused by amyotrophic lateral sclerosis (ALS), to replace or restore impaired communication or motor functions in clinical trials. A large number of studies have explored brain activities during movement execution where the kinematic parameters are correlated with the cortical processes [2][3].

More recently, decoding of brain signatures before motor execution, i.e., pre-movement states, has attracted more attentions since this information can be used to predict actions or anticipate the events. A BCI system can detect the user's intention from non-invasive EEG signals and convert it into control signals to the external device. There have been closed-loop applications such as triggering peripheral electrical stimulation (ES) [4], controlling an orthosis [5], driving a wheelchair [6], and actuating a powered exoskeleton [7]. For these systems, an early detection of the movement intention from the user could be a prerequisite to close the perception-action loop.

The cortical process of movement intention involves two modalities of EEG correlates, e.g., the motor-related cortical potentials (MRCPs) and sensorymotor rhythms (SMRs) including event-related desynchronization/synchronization (ERD/S). Both of them have the advantage of high temporal precision and anticipation properties even for movement imagination or motor attempt, therefore compatible for the control signals to build an intuitive and natural BCI. SMR-based method has been used to predict human voluntary movement in real-time with a small false positive rate [8]. Another work by Pfurtscheller and Solis-Escalante indicted that the beta rebound (ERS) over central middle line during foot motor imagery (MI) was relatively stable and reproducible in single EEG trials [9]. Although these SMR phenomenons are suitable to realize a a brain switch, long training is required for some users to learn to optimize the modulations of their brain patterns.

On the other hand, movement-related cortical potentials (MRCP) has been employed in recent studies for the detection of pre-movement states, e.g., reaching movement [10], ankle dorsiflexion [11] and sitting/standing transition [12]. The MRCP is produced in corporation with movement planning and execution, with less training procedures. When generated in self-paced paradigms, it is termed as Bereitschaftspotential (BP) or readiness potential [13]. Being a slow cortical potentials (SCPs) close to DC, BP is elusive to present, which makes it challenging to detect from the background EEG activities.

A possible way to boost the detection performance is to combine the MRCP-based and SMR-based methods. Interest has been devoted to studies about the upper-limb movement intention using both features [14], while the lower-limb work is still missing. In this paper, we present a BCI to detect lower-limb movement intention combining the complementary information from MRCP and SMR with a support vector machine (SVM) classification model. We analyzed the features and brain pattern modulations during self-paced pre-movement states. The decoder was implemented in both BCI command sending and single-trial basis, which makes it practical relevance for neurorehabilitation scenarios.

II. Methods

A. Experimental protocol

Five subjects (four male, with age 25.2 $\pm$ 1.7) participated in the experiment. All subjects were naive BCI users with normal or corrected-to-normal vision. No known neurological or psychiatric diseases were reported among them. The experimental protocol was approved by the local ethical committee

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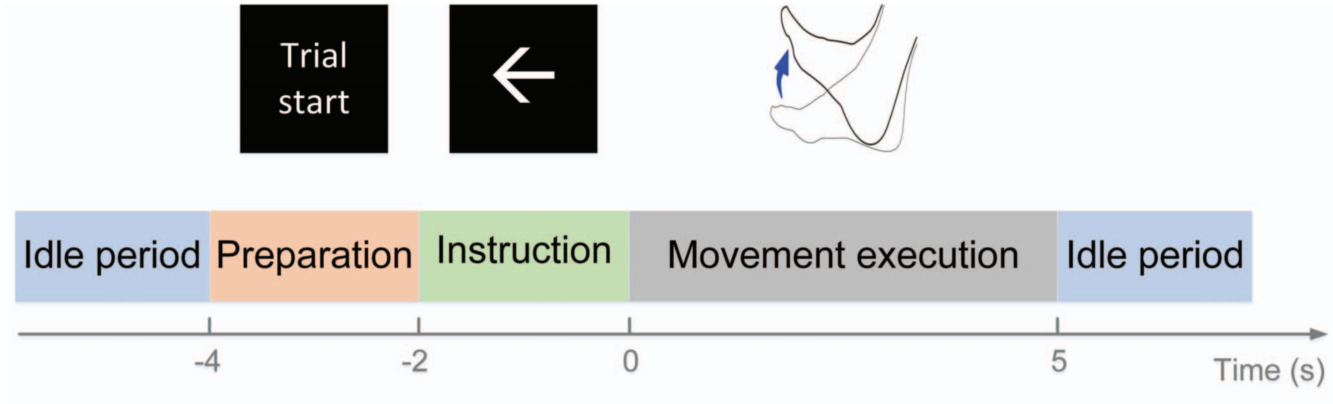

Fig. 1. Experimental protocol. Each trial started with a preparation phase (baseline), followed by a 2-s instruction phase and 5-s movement execution phase. The subject performed self-paced ballistic ankle dorsiflexion during the movement execution period.

in accordance with the Declaration of Helsinki. All participants signed a written informed consent.

All the experiments were conducted in the laboratory conditions to minimise additional sources of noise. Participants were comfortably seated in front of a computer screen, which showed the instructions during the experiment. The distance from the inion to the nasion and between both ear contours were first measured, to keep the electrode Cz exactly on the vertex of the cap. During an experimental session, the subject performed 4 runs consisted of altogether 200 trials, with a long rest in between. Figure 1 illustrates the protocol with the timeline for each trial, composed of preparation, instruction and movement execution phases. The directions of the arrows were recorded in a local file with left and right shuffled and balanced within each run.

B. Data acquisition

EEG signals were recorded from 9 positions (FC1, FCz, FC2, C3, Cz, C4, CP1, CPz, and CP2, according to the international 10/20 system) by using active scalp Ag/AgCl electrodes with multi-pole connectors, as shown in Figure 2. The ground electrode was located at the forehead (position Fpz), and the reference electrode was placed on the right earlobe. The EEG was amplified, digitalized with a sampling frequency of 256 Hz, power-line notch filtered, and bandpass filtered between 0.1 and 100 Hz (g.USBamp, g.Tecgmbh, Austria).

Surface EMG was recorded by using disposable Ag/AgCl electrodes, which were pre-gelled and self-adhesive. Two pairs of EMG electrodes (4 channels) were placed on the tibialis anterior (TA) muscles of both legs with bipolar derivations. Moreover, EOG signals were acquired from 3 electrodes positioned above the nasion, and below the outer canthi of the eyes. This configuration was able to capture both horizontal and the vertical ocular components.

All the 16 electrophysiological channels were connected to the inputs of g.USBamp amplifier, so that all the components had common ground and reference. These electrodes were combined in one ribbon cable that can be directly connected

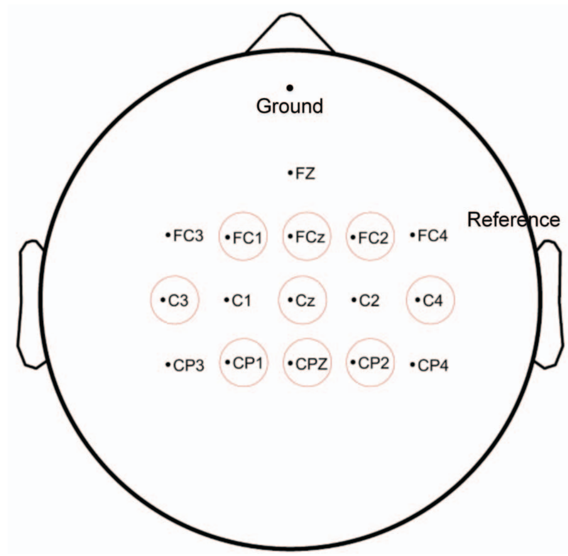

Fig. 2. Scalp map to show the EEG montage during the experiment when seen from the top. All the electrodes were placed over the sensorimotor cortex.

to system connectors of the amplifiers. Data acquisition was accomplished through labstreaminglayer (LSL) (`https://github.com/sccn/labstreaminglayer`) by Swartz Center for Computational Neuroscience, UCSD. It was based on multi-modal time-synched data transmission over local network. Graphical interface and signal recording were developed with a customized Python script (`https://c4science.ch/diffusion/1299/`). In all cases, the signals were synchronized with the trigger channel by a USB to LPT adapter. Signal processing was conducted through Python and Matlab R2015b (by MathWorks, US) with EEGLAB 13.5.4b toolbox, placed on an Inter Core i5-2430M processor at 2.40 GHz with Windows 7 operating system (OS).

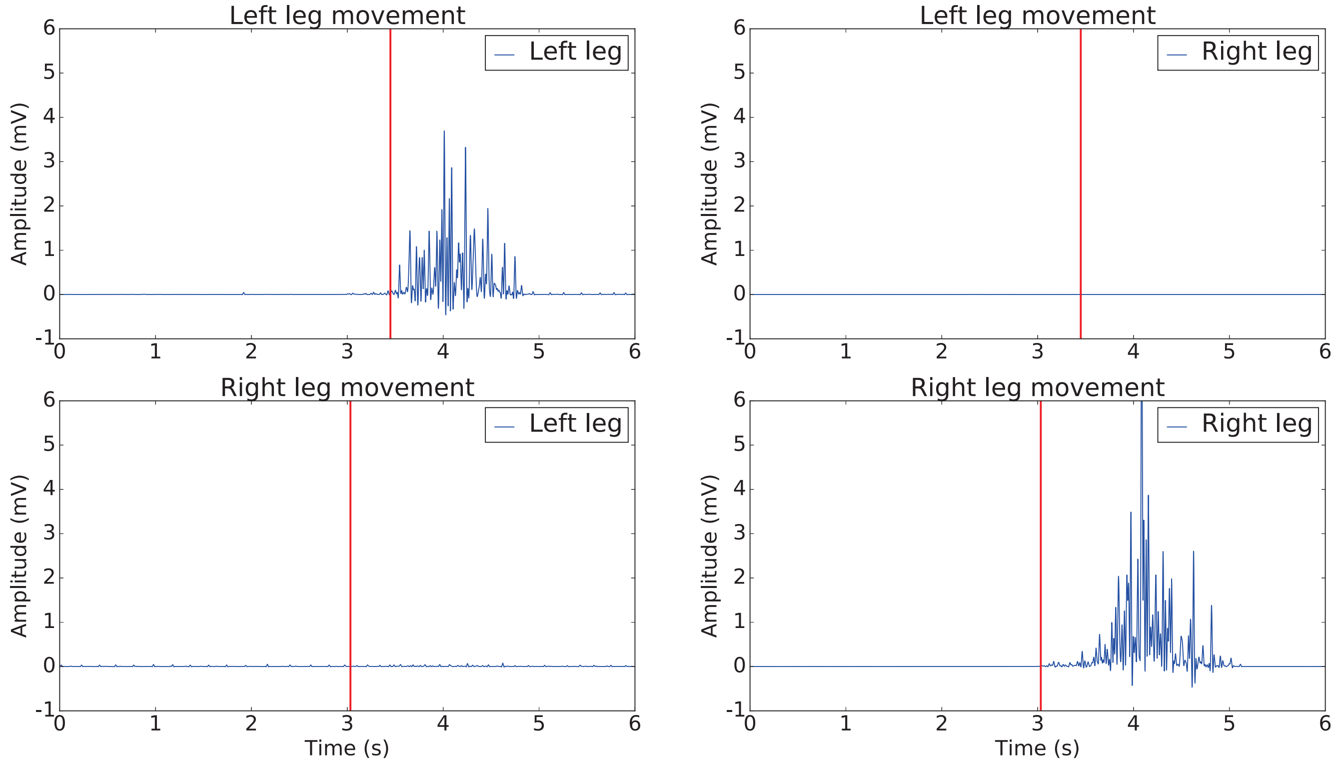

Fig. 3. Representative samples of actual movement onset detection for left (upper panel) and right leg movement (bottom panel) based on the TKEO conditioning and threshold-based method.

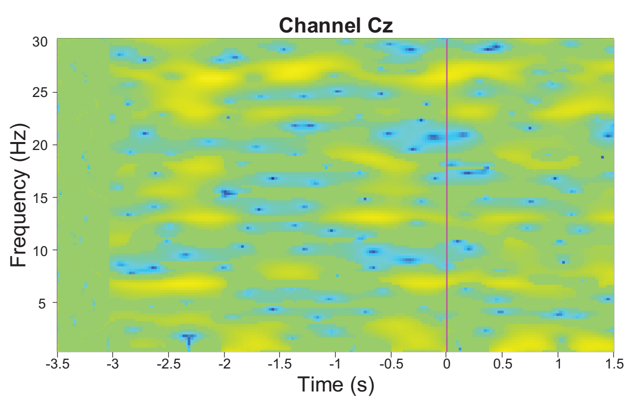

Fig. 4. Time-frequency representation at 0.1-30 Hz over Cz channel.

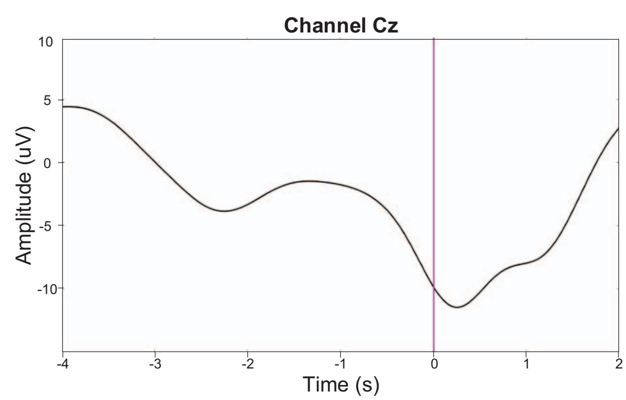

Fig. 5. Time-amplitude representation at 0.1-1 Hz over Cz channel.

C. Detection of actual movement onset

The EMG data was exploited to detect the time when each movement started using a threshold-based method [15]. The signal was first high-pass filtered at 30 Hz (6th order Butterworth), rectified and low-pass fitered at 50 Hz (2nd order Butterworth) to obtain smoothed envelope. Then the data was processed by a discrete Teager-Kaiser energy operator (TKEO) defined as:

$$\psi[x(n)] = x(n)^2 - x(n-1)x(n+1) \tag{1}$$

where x is the EMG value and n is the sample number. After applying TKEO, we calculated a threshold as

$$T = \mu + h\theta \tag{2}$$

where μ and θ are mean and standard deviation of the signal from the instruction period, and h is the threshold level which was empirically set to 10. The actual movement onset was identified as the first time point when more than 20 consecutive samples exceeded the threshold T.

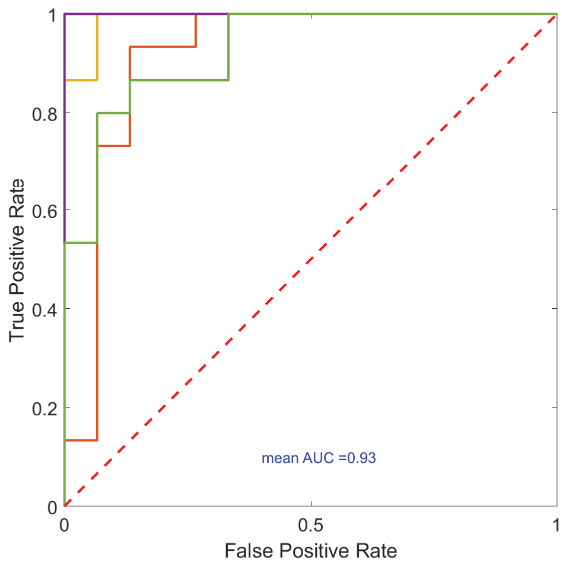

Fig. 6. Sample-based classification performance of a typical subject (S1). The dotted red line represents chance level and each solid line displays the ROC curve from one fold. The mean AUC value is shown at the middle bottom.

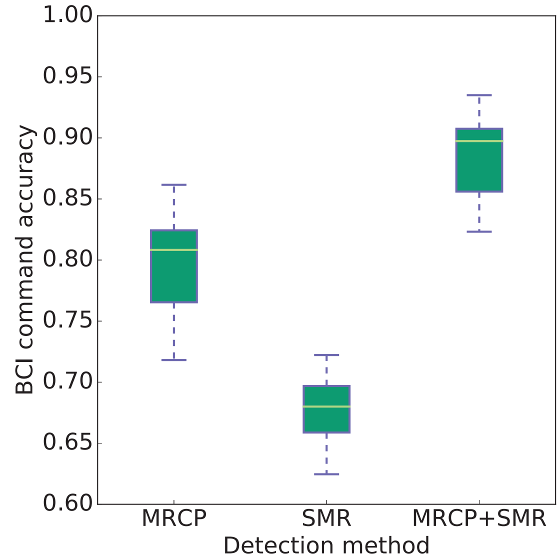

Fig. 7. BCI command sending accuracy using MRCP, SMR and MRCP+SMR based methods, averaged over all subjects.

D. *Electrophysiology analysis*

SMR and MRCP were investigated to evaluate the pre-movement cortical activities. For SMR analysis, the EEG data was filtered with a zero-phase fourth-order Butterworth at 0.1-30 Hz and then segmented into 6-s epochs from -4 to 2 s with respect to the actual movement onset. The time-frequency representation was calculated using Morlet wavelets with a resolution of 0.5 Hz. The significant event-related spectral perturbation (ERSP) maps were computed using a baseline interval between -3 to -2 s with a bootstrap analysis and Bonferroni corrected (α = 0.05).

For MRCP analysis, the EEG signal was filtered with a Butterworth second-order forward and backward band-pass filter at 0.1-1 Hz. Epoching was the same as SMR analysis and each epoch was baseline corrected with the average activity over the baseline period.

E. *Feature extraction and classification*

For SMR-based method, a Laplacian spatial filter was first applied on the signal to enhance the signal-to-noise ratio (SNR). The power spectral density (PSD) of each trial was calculated over 1-s time window every 62.5 ms using Welch method with 3 overlapped Hammming windows of 750 ms. The features in the frequency domain were estimated between 1 to 30 Hz with a resolution of 1 Hz. Given the number of EEG channels, each sample comprised 270 features.

For MRCP-based method, the EEG signal was common average referencing (CAR) filtered, subsampled to 16 Hz and then processed with a narrow band pass IIR filter with cutoff frequencies of 0.1 and 1 Hz. Considering the channel number and sample frequency, each sample was composed of 144 features. Therefore, the feature vectors of each time window consisted of 414 values.

After extracting the features, we performed a feature selection process for each subject to maximize the separability of the two mental tasks, i.e., movement preparation and baseline period. The discriminant power (DP) of each feature was estimated using the Fisher score:

$$r = \frac{|m_1 - m_2|}{(s_1 + s_2)} \tag{3}$$

where m_i and s_i are the mean and variance of the samples from each class. Subsequently, the features were ranked based on the values of r. We selected 10 features per subject based on the DP as well as neurophysiological evidence on the neural signature. We used SVM to classify movement preparation and baseline epochs. Sequential minimal optimization (SMO) was applied to solve the optimization problem. It reduced the computational complexity by subdividing the mathematical problem of convex quadratic programming into subproblems. Sample-based classification was conducted using 5-fold cross validation, where chronological orders of the data were maintained. The result was reported with an area under the curve (AUC) in the receiver operating characteristics (ROC) space, which represented the trade-off between the false positive rates (FPR) and true positive rates (TPR). In order to get a more robust decision at the trial level, evidence accumulation was applied on the computed likelihoods for each sample. It was a smoothing processing computed as:

$$p_t = \alpha * p_{t-1} + (1 - \alpha) * p_t \tag{4}$$

where p_t is the integrated probability at time t and α is the smoothing factor. Delivery of BCI command is performed only when a certainty threshold was reached. Smoothing factor and threshold were defined based on the performance of each subject. Furthermore, latency was evaluated in single-trial basis. The performance was estimated over 1-s time

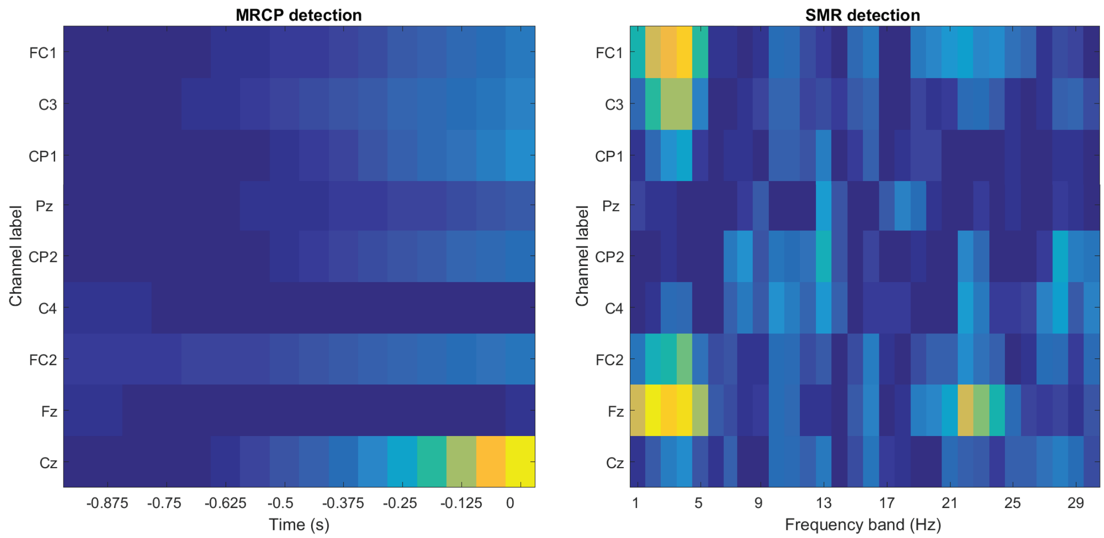

Fig. 8. Features selected by Fisher score with MRCP-based model (left panel) and SMR-based model (right panel). For MRCP detection, features are time windows and channels. For SMR detection, features are frequency band and channels.

window shifted every 125 ms from -2 to 1 s with respect to the actual movement onset. We used the same feature selection (Fisher score) and classification (SVM) method as BCI command sending processing. The chance level was calculated by shuffling the training labels and repeated the cross validation for 1000 times. We selected the first time point as detection latency when consecutive 5 samples had TPR significantly above chance level (two-sample t-test, $p < 0.05$).

III. Results

Actual movement onset was detected from the muscle activities based on the threshold-based method with TKEO conditioning. Representative samples of the detection are shown in Figure 3. Trials with an early reactions (less than 2 s after instruction period) or contaminated with eye movement (inspected by the EOG channels) were removed, resulting in an averaged 193 epochs over the subjects. We then pooled the data of left and right leg movement for the purpose of detection.

Figure 4 and 5 present the electrophysiology processes for SMR and MRCP, respectively. Time-frequency representation indicates significant ERD activity over μ (8-12 Hz) and low beta band (14-22 Hz) at Cz channel (two-sample t-test, $p < 0.05$, Bonferroni correction). Besides, grand average MRCP correlates display a negative deflection starting 1 s before movement onset and reaching maximum negativity after the onset. This is in consistent with previous works on the neural signatures of movement intention decoding [10][14].

The sample-based classification performance of a typical subject is shown in Figure 6. The average AUC across subjects (N = 5) is 0.88 ± 0.52. Three subjects reached a mean AUC above 0.90, with the best performance of 0.96. The average BCI command accuracy over all subjects was 0.89 ± 0.04, obtained by the combined features from SMR and MRCP. Furthermore, a comparison of different detection models concerning BCI command accuracy was conducted, as shown in Figure 7. We found statistical significance (one-way ANOVA with factor accuracy, $p < 0.01$) between the models. Multiple comparisons with the Tukey-Kramer critical value showed that the model combining MRCP and SMR significantly performed better than the model with the separate features.

As the feature was automatically selected by Fisher score, a post-hoc feature analysis was conducted to show the information exploited in the models. Figure 8 shows the DP of the features averaged across all subjects. The features are channel-time pairs for MRCP and channel-frequency pairs for SMR. The most discriminative features are the time windows from -0.125 to 0 s with respective to movement onset over Cz channel for MRCP. These features are coincide with the negative deflexions of the EEG trace. On the other hand, bins in the low frequency band over Fz and C3 are more often selected by SMR models. Therefore, complementary information was used by the two models with a boosting performance obtained by the combination of the two features.

Finally, movement onset detection was performed in single-trial basis to calculate the detection latency. Figure 9 shows the results of a typical subject with the green vertical line indicating the detection latency. Movement intention was detected above chance level across the subjects on average at -0.325 ± 0.127 ms before actual movement onset. The average maximum TPR was 0.84 ± 0.03, peaking on average 10 ms before movement onset.

IV. Discussion and Conclusion

In this study, we proposed a BCI framework combining SMR and MRCP for the detection of lower-limb movement intention. Experiment was conducted with healthy subjects

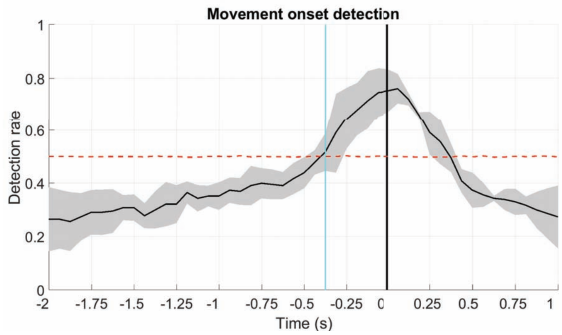

Fig. 9. Single-trial detection of movement onset of a typical subject (S3). The solid black line and grey shaded regions depict the mean and standard derivation of the detection rate at each point. Red dashed line indicates the random performance. The green line shows the movement onset detected from the EEG by the proposed model.

demonstrating the applicability of the paradigm with sample-based, BCI command sending, and single-trial performance. In particular, we show the combination of the features extracted from the cortical rhythms and SCP can boost the performance to detect the voluntary movement onset.

Previous studies have described several aspects of the movement onset detection. Upper-limb reaching movement was decoded by Lew et al with an average maximum TPR of 0.76 $\pm$ 0.07 and detection latency of 460 $\pm$ 85 ms before actual onset [10]. A recent study by Xu et al proposed a detection model with advanced dimensional reduction method and LDA classifier, resulting in a TPR of 0.79 $\pm$ 0.12 and latency of 315 $\pm$ 165 [16]. A direction comparison of these results could be difficult due to the difference of the protocols and subject variations. Nevertheless, significantly better performances had been achieved with the combined features in all metrics with the same dataset.

In order to build a brain switch for closed-loop BCI, the robust detection is critical. Currently, we obtained promising results with the classification model based on SVM. Further work need to be done with either simplified or more sophisticated signal processing and machine learning techniques. On the other hand, the decoded signal can be used to trigger external devices, e.g., exoskeleton. Further work should be done to provide real-time feedback to the user during the recordings. In this sense, the subjects could learn to modulate their brain modulation for a more effective training.

Compared with upper-limb studies, lower-limb movement decoding is more challenging due to less distinctive patterns. However, lower-limb movement intention detection is practical relevance for walking and gait rehabilitation. Although tested with healthy subjects as a proof of concept, our results need to be corroborated on patients or end-users as a step further towards the practical neurorehabilitation environments.

In conclusion, we proposed a BCI to detect self-paced lower-limb ankle dorsiflexion combining the features from MRCP and SMR. An experiment with healthy subjects revealed the applicability of the proposed framework to build a brain switch towards clinical population.

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