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Detection of Movement Related Cortical Potentials from Single Trial EEG Signals

Eda AKMAN AYDIN

Gazi University Faculty of Technology, Department of Electrical and Electronics Engineering, 06500, Beşevler/ANKARA

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Abstract

Movement-Related Cortical Potentials (MRCPs) are signals that begin to appear approximately two seconds before the onset of voluntary movements and can be recorded with EEG. MRCPs are important signs that the movement will begin. By using MRCPs, brain-computer interface (BCI) users' movement intention can be determined preceding movement onset and this sign can be used as a control signal for BCI systems. Determining the movement intention before the movement execution is extremely important information, especially for real-time BCI systems. In this study, it is aimed to improve the detection accuracy of MRCPs by using single trial EEG signals and thus to distinguish between the movement and resting states of BCI users with high accuracies. Furthermore, the effects of pre-processing steps, such as filter cut-off frequencies, number of electrodes, and MRCP time window on the success of distinguishing movement/resting states are investigated. For this purpose, Katz's fractal dimension and nonlinear support vector machine methods are used in the feature extraction and classification stages, respectively. The proposed method is tested on the attempted hand and arm movements dataset containing EEG signals of 10 participants with spinal cord injury. Katz's fractal dimension and support vector machines methods can determine movement and resting states with an average of 96.47% accuracy using MRCP signals. If the number of electrodes to be used in signal analysis is 3, 9 and 61, the obtained accuracy rates are determined as 83.71%, 90.67%, and 96.47%, respectively. The experimental results also showed that the filter cut-off frequencies used in the pre-processing has a significant effect on the accuracy.

1. INTRODUCTION

Brain Computer Interfaces (BCIs) are systems that enable direct communication between the human brain and machines. By analyzing the brain activity of the human brain that changes with the intention, a BCI can convert these changes into commands associated with the user's intention [1]. BCI systems generally involve four main units: data acquisition, signal processing and feature extraction, classification, and output devices. The data acquisition unit is used to record the brain activity using electrical, optical, or magnetic imaging techniques. Among these imaging techniques, electroencephalograph (EEG), which records the electrical activity in the brain, is one of the most widely used techniques due to its non-invasiveness, portability, and low cost [2].

In BCI systems, various signals observed in brain activity related to processes such as movement, perception, focusing and calculation are used as control signals [3]. The P300 components of event-related potentials, motor execution/imagery signals, and steady-state visual evoked potentials (SSVEP) are commonly used signals in BCI systems [4–6]. The mechanism of the origination of each of these signals in the brain is different from each other. P300 potentials are signals of positive amplitude that appear approximately 300 ms after encountering a rare stimulus [4]. SSVEP is the same frequency oscillation seen in the occipital lobe of the brain at the moment of focusing on a stimulus of a certain frequency [5]. Motor execution/imagery signals are the changes in the signal frequency that occur in the sensorimotor areas of

*Corresponding author, e-mail: edaakman@gazi.edu.tr DOI: 10.29109/gujsc.1083912

the brain when users execute or imagine a movement [6]. The signal that will be used in BCI systems is determined by considering system expectations such as the application to be controlled, the number of commands to be produced, training time, endogenous/exogenous signal requirements, and the number of electrodes that can be used. Although these signals are the most commonly used signals in BCI applications, it has been seen that recently, movement related cortical potentials (MRCPs) are also frequently used signals in BCI systems. Being an endogenous signal, being easily used by people without BCI experience, and therefore requiring low individual user training time, can be listed among the advantages of MRCPs [7–8].

MRCPs are low-frequency negative amplitude deviations that can be observed in the EEG signal, occurring approximately 2s before the onset of a voluntary movement. MRCPs occur due to the cortical processes used in the planning and/or preparation of the movement before the movement execution. The occurrence of the signal before the movement means that there is no muscle movement yet, but the user is planning an action in the near future. In this process, the cortex adapts to the execution of the movement and the signal occurs in a period of about 0.5–2 s before the start of the movement [9]. MRCPs are formed during both the execution of the movement and the imagination of the movement. MRCPs have been studied in healthy people and people with neurodegenerative diseases, and it has been observed to occur in both groups during motor tasks [8]. In recent studies, it is seen that MRCPs are used to determine upper limb movements [10–11] and to analyze the speed and strength of movement of BCI users regarding limb movements [12–13]. As they are signal that determine the start of movement before the movement, MRCP signals are generally used as a key to indicate the start of movement in BCI-based studies [14].

Since MRCPs are important markers of the onset of movement in BCI systems, the reliable and efficient determination of single trial MRCPs with high accuracy is especially important in real-time BCI applications [8, 15]. However, MRCP signals may be contaminated due to the low signal-to-noise ratios of EEG signals, low-frequency motion artifacts, and electroculogram (EOG) signals with similar frequency bandwidths to MRCPs [8]. Various signal processing and classification methods have been proposed to resolve this problem [15–19]. Ofner et al. [16] used shrinkage regularized linear discriminant analysis (sLDA) classifier, which was embedded in the discriminative spatial pattern (DSP) method, to determine movement and resting states in their study on 15 healthy subjects. In the study, they were able to distinguish between movement execution and resting states with 85% accuracy, and between movement imagination and resting states with 73% accuracy. Applying a subject-dependent and section-wise spectral filtering (SSSF) method, Joeng et al. [21] were able to distinguish between hand movements and resting states with 73% accuracy, and lower limb movements and resting states with 86% accuracy. Ieracitano et al. [19] suggested a deep convolutional neural network to discriminate the phases of preparation of hands' movements (open/close) from the resting state, and they were able to determine hand movement and resting states with an average accuracy of 90%. Results of the studies indicate that although MRCP signal can be used to determine movement/resting states, for adapting BCI systems to practical real-time applications, it is required to improve the accuracy rates obtained in these studies.

In the literature, in order to determine MRCPs, several preprocessing techniques and electrode combinations are employed. In order to examine the effect of the filters in the preprocessing stage, Karimi et al. applied filters such as constrained ICA (cICA), common spatial filters (CSP), Laplacian spatial filter (LAP), and revealed that cICA resulted in high accuracy rates [36]. On the other hand, EEG signals recorded in studies that are carried out to determine MRCPs are filtered using band-pass filters at various cut-off frequencies [15]. In these studies, it is seen that the upper cut-off frequencies of the filters used in these studies are ranging from 5–100 Hz and there is no consensus on the filter cut-off frequencies during the preprocessing stage. Besides, it is seen that different electrode combinations containing 1–128 electrodes are used in the determination of MRCP signals. Among these combinations, it is seen that commonly used electrode combinations are in the positions such as C3, Cz, and C4, and Fz, Cz, Pz, C3, and C4. The results of the studies show that MRCP signals together with appropriate electrode combinations and signal processing techniques, can provide major information on the initiation of movement [15].

Detection of MRCP signals with high accuracy is important in real-time BCI systems in terms of determining the user's movement intention. However, it is seen that there is no consensus on the preprocessing stages of MRCP signals in the literature. In this study, it is aimed to improve the accuracy of the determination of movement and resting states by using MRCPs in single trial EEG signals. Additionally, the effects of filter cutoff frequencies, the number of electrodes used and the time window that contains pre-stimulus and post-stimulus times of MRCP signal on the accuracy of determining movement and resting states were investigated. To that end, Katz Fractal Dimension (KFD) method was used for feature extraction and Support Vector Machines (SVM) method was used as the classifier. The proposed method was tested on the attempted hand and arm movement dataset recorded from SCI patients by Ofner et al. [24] The results of the study revealed that MRCP signals can be classified with high accuracy together with the KFD and SVM methods.

In the second section of this study, movement related cortical potentials are briefly introduced, the dataset and the methods used are explained in the third section, the experimental results are presented in the fourth section, experimental results are discussed in the fifth section and the results of the study are summarized in the last section.

2. MOVEMENT RELATED CORTICAL POTENTIALS

Movement related cortical potentials are additive cortical activity that occurs at the time of movement and can be detected by electrodes placed on the scalp. MRCPs are low-frequency (0-5Hz) negative shifts in the EEG signal, with amplitudes between 5-30 μV. Contrary to other evoked potentials, the formation of movement-related potentials continues for 1.5-2s before the stimulus and 0.5-1s after the stimulus. MRCPs occur in relation to movement planning and preparation for movement and occur approximately 2 seconds before a voluntary movement [20].

MRCP signal consists of three components, which are thought to reflect movement planning/preparation, movement execution, and movement control performance. These three components are Bereitschaftspotential called readiness potential (BP), motor potential (MP) and movement monitoring potential (MMP), respectively. MRCP occurs both during the movement execution and the movement imagination. MRCP signals and components that occur during movement execution and movement imagery are shown in Figure 1 [15].

Components of the MRCP signal can be affected by a variety of factors, such as the speed of movement repetition, speed and precision of movement, perceived effort, applied force, discreteness and complexity of movement, learning and skill acquisition, brain structures, and pathological injuries [22]. MRCP may also differ according to the limb in which the movement occurs, movement in the limb, individuals, and patient groups [23]. Particularly, the fact that it differs according to the limb and the movement in the limb enables MRCP signals to be used as a control signal in BCI applications related to movement.

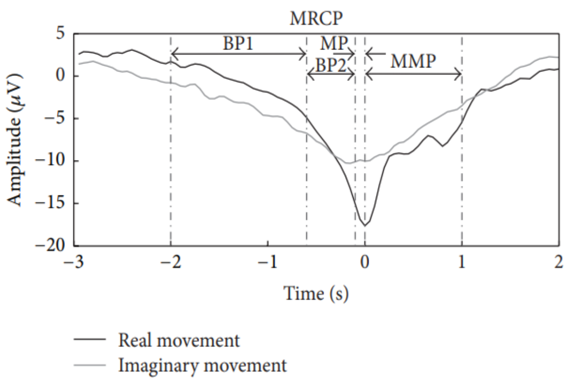


Figure 1. *MRCP components of a healthy participant for ankle dorsiflexion and imaginary ankle dorsiflexion [15]. MRCP signals were obtained by averaging the filtered EEG signals recorded from the F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4 electrodes. 0s indicates the moment when the movement started.*

3. METHODOLOGY

3.1. Attemped Hand and Arm Movements Dataset

In this study, Attempted Arm and Hand Movements Dataset collected by Ofner et al. [24] was used. The dataset includes EEG signals recorded from 10 participants with spinal cord injury. All participants were right-handed and all but participant 7 used their right hand during the experiments. The participants' demographics and degree of illness can be accessed from the study [24].

EEG signals were recorded using 61 electrodes placed in the frontal, central, parietal and temporal regions. The reference electrode was placed on the right earlobe and the ground electrode was placed on the AFF2h point. Data were recorded with 256 Hz sampling frequency, using 8th order 0.01–100 Hz Chebyshev filter and 50 Hz bandstop filter.

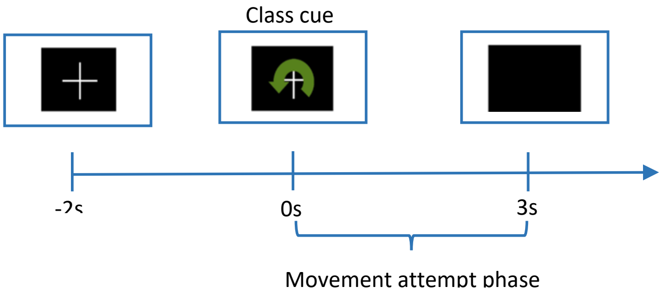


Figure 2. *Process sequence for a trial during data recording for dataset [24]*

During data recording, commands were given to the subjects via the computer screen. Each round starts with the display of a (+) sign on the screen and the beep sound. The subjects were first asked to focus on the plus sign displayed on the computer screen during the entire trial, which lasted for 5 seconds. Two seconds after the start of the trial period, the cue for the movement requested from the subjects was displayed on the screen for 3 seconds. The sequence of processes for a trial during data recording is shown in Figure 2. During the experiments, subjects executed or attempted the movement according to their remaining motor abilities. The data were collected for 5 movements such as, pronation, supination, palmar grasp, lateral grasp, and hand opening

In the dataset, a session consists of 9 rounds with 40 trials. Therefore, each session includes 72 trials for all movements. Except for 9 rounds involving movement and attempted movement trials, 3 rounds of resting state sessions lasting 70 seconds were recorded from all participants. In the experiments, EEG signals related to supination and palmar grasp movements, which are in different joints, are used to generate movement state data.

3.2. Katz's Fractal Dimension (KFD)

Fractal dimension (FD) is a measure of self-similarity. FD algorithms try to determine the number of times a pattern is repeated in time series and in this way measure the self-similarity of the content in the signals and reflects its complexity [25]. FDs are used in the diagnosis of diseases such as autism, epilepsy, schizophrenia, and Alzheimer's, as well as determining mental workload levels, emotional and cognitive changes by using EEG signals [26,27]. On the other hand, it has also been used for feature extraction in BCI systems based on the use of EEG and fNIRS signals [27, 28].

KFD is a low computational cost FD algorithm that uses the distance between consecutive points. KFD, a measure of irregularity in a one-dimensional time series signal, can be derived directly from the signal waveform. For the time series $x_1, x_2, \ldots, x_N$, KFD can be calculated by Equation 1. In Equation 1, L is the total length of the curve and d is the diameter estimated as the distance between the first point of the array and the point of the array providing the furthest distance. d and L are calculated by Equations 2 and 3, respectively. The normalized KFD is given in Equation 4, where $n = L/a$ is the number of steps on the curve [25,29].

$$KFD = \frac{log_{10}(L)}{log_{10}(d)} \quad (1)$$

$$d = maksimum(|x_1 - x_j|) \qquad j = 2,3, \ldots \mathrm{N} \quad (2)$$

$$L = \sum_{i=2}^{N} x_i - x_{i-1} \quad (3)$$

$$KFD = \frac{log_{10}(n)}{log_{10}(n) + log_{10}(\frac{d}{L})} \quad (4)$$

3.3. Support Vector Machines

Support Vector Machines (SVM) are one of the commonly used methods for the classification of EEG signals in BCI systems [30–32]. SVM is a supervised classification algorithm that makes use of labeled training examples. SVM is a classification method designed to determine a hyperplane that maximizes the distinguishing distance between samples representing two different classes. For a linear classifier, the hyperplane is expressed by the equation $wx + b = 0$. In this equation, w is the weight vector, x is the input vector, and b is the bias. SVM uses instances called support vectors located at the endpoints of the classes to distinguish between the two classes. The purpose of SVM is to determine the optimum hyperplane that provides the maximum margin to separate these two classes. The maximum margin between support vectors can be achieved by minimizing $\|w\|$ [33–35].

In cases where the data cannot be separated linearly, it must be moved to a higher dimensional feature space where it can be decomposed. Kernel functions (K) are used to transfer data to another space. The Gaussian kernel is one of these kernel functions and is defined by Eq. 5. The selection of the parameter σ, which determines the width of the Gaussian kernel function, is important in order to solve the problem in the best way [33–35].

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2}) \quad (5)$$

4. EXPERIMENTAL RESULTS

In this study, KFD and SVM methods were proposed to determine the movement and resting states of participants by using MRCP signals. The success of the proposed method has been tested on the Attempted Hand and Arm Movements dataset. The grand averages of the EEG signals recorded from the Cz position regarding supination, palmar grasp movements, and resting states for Subject 3 in the dataset are shown in Figure 3.

In the study, a bandpass filter with a cutoff frequency of 0.3–50 Hz was applied to the EEG signals in the preprocessing stage. The filtered EEG signals were divided into windows to cover the 2s before the stimulus and the 1s after the stimulus. KFD was calculated for 61 channels used during data recording. The distributions of the KFD values calculated for the Cz-Pz and Fz-Cz electrodes related to the movement and resting states are shown in Figure 4. a and b, respectively.

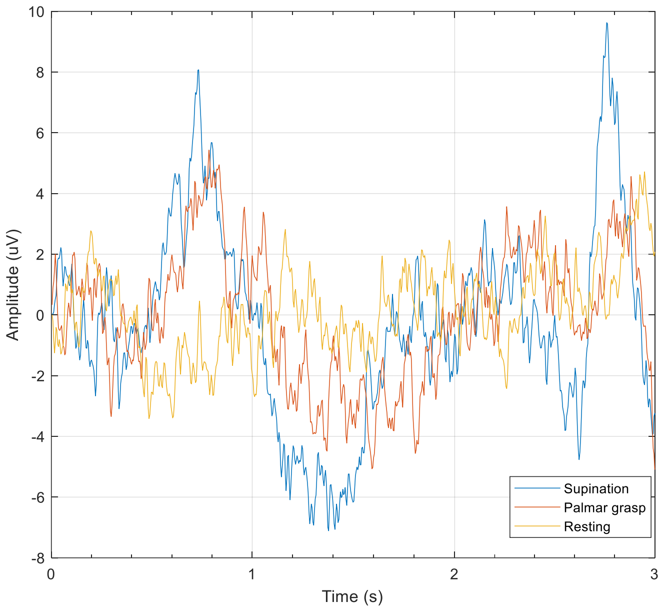
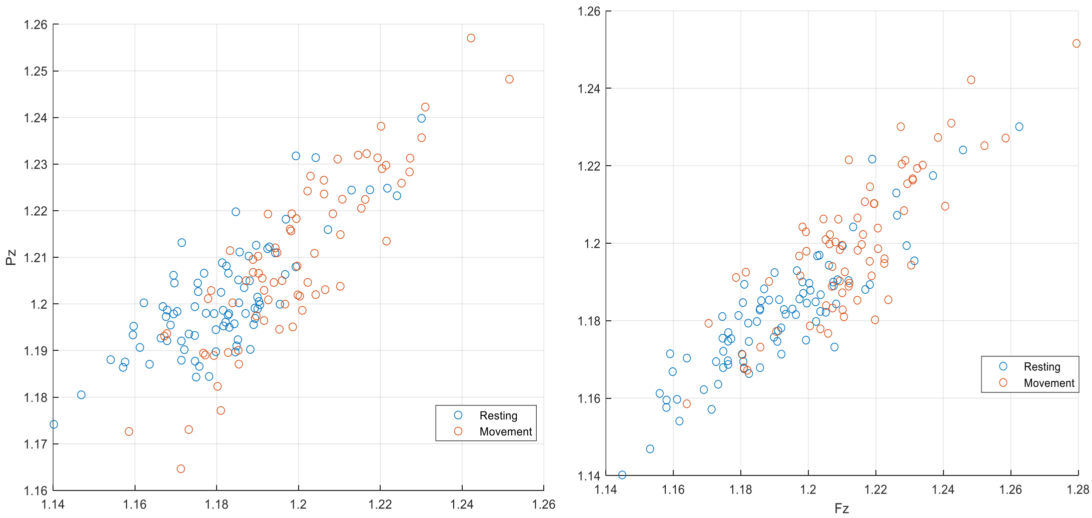


Figure 3. *The large averages of EEG signals recorded from the Cz position regarding supination, palmar grasp movements, and resting states*

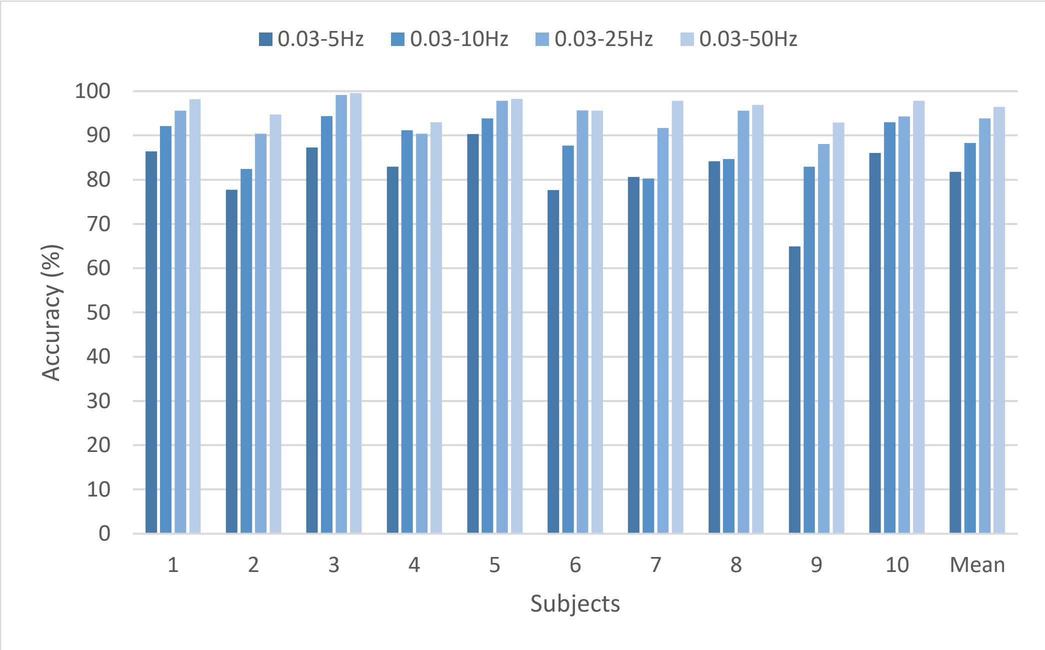
Nonlinear SVM classifier was used in the classification phase. The Radial Basis Function was used together with the Gaussian Kernel Function (GKF) in the creation of the nonlinear SVM. In order to use the classifier with the highest performance, participant-specific optimum sigma and C parameters were determined individually. During the performance evaluation of the classifiers, 10-fold cross-validation was applied.



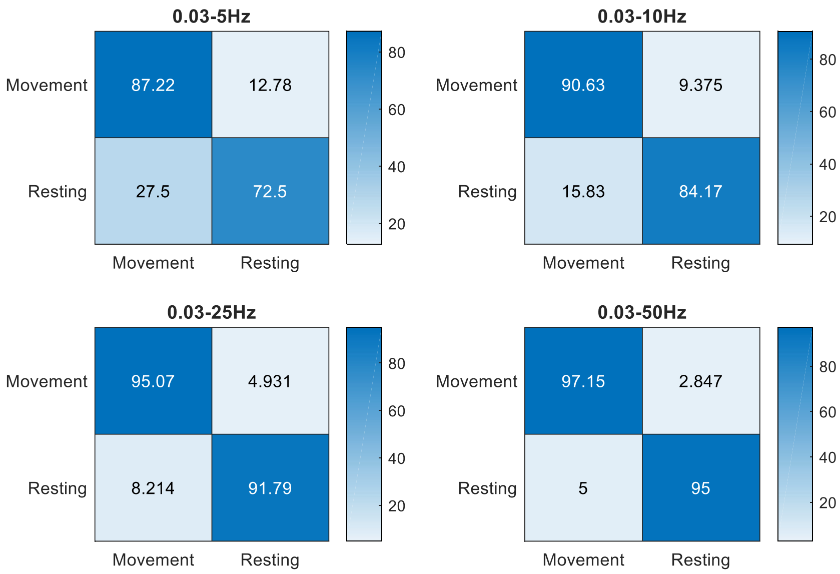
(a) *(b)*

Figure 4. *Distributions of KFB values calculated for movement and resting states from positions (a) Cz-Pz (b) Fz-Cz*

In order to examine the effect of filter cut-off frequencies in determining the movement and resting states by using MRCP, the classifier accuracies were examined in case the upper cut-off frequencies of the filter were used as 5Hz, 10Hz, 25Hz, and 50Hz, respectively. In the selection of the cutoff frequencies, the cutoff frequencies used in the studies in the literature were considered. The classification accuracy rates for the selected four frequency bands and 10 subjects are shown in Figure 5.a. According to Figure 5. a, it has been observed that classifier accuracies increase when the upper cutoff frequency of the bandpass filter increases for all subjects. Classification accuracies for 5Hz, 10Hz, 25Hz, and 50Hz cutoff frequencies were determined as 81.80%, 88.25%, 93.85%, and 96.47%, respectively.



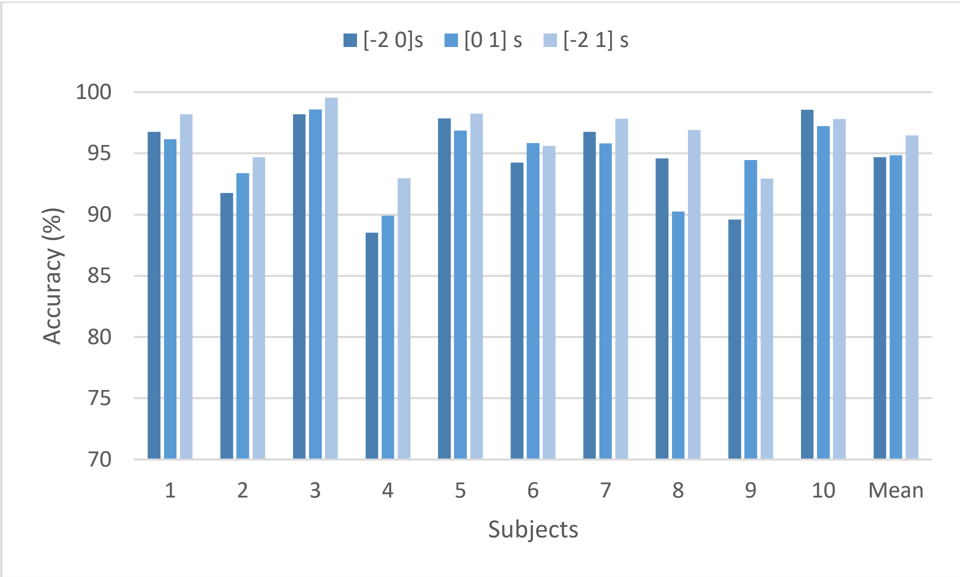
(a)



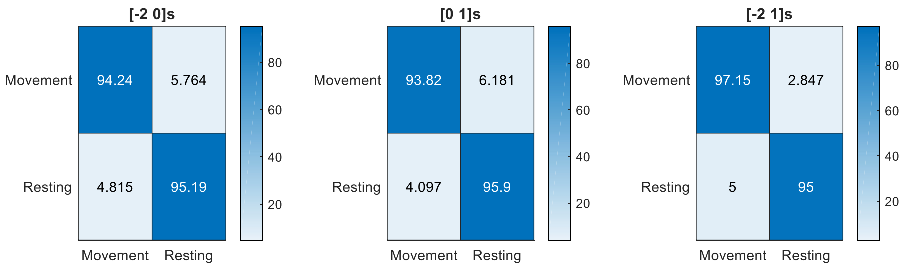
(b)

Figure 5. *(a) classification accuracies (b) confusion matrices, for the filter upper cut-off are 5Hz, 10Hz, 25Hz, and 50Hz*

In Figure 5. b, the confusion matrices for four different cutoff frequencies are given. Accordingly, the movement state detection accuracies for the 5Hz, 10Hz, 25Hz, and 50 cut-off frequencies were 87.11%, 90.63%, 95.07, and 97.15%, respectively. The resting state determination accuracy was determined as 72.5%, 84.17%, 91.79%, and 95%, respectively. Although the movement state was determined with higher accuracy than the resting state for all four cut-off frequencies, it is seen that both movement and resting states are classified with high accuracy.



(a)



(b)

***Figure 6.** For three different time intervals covering pre-stimulus 2s, post-stimulus 1s, pre-stimulus 2s, and post-stimulus 1s time intervals, (a) classification accuracies (b) confusion matrices*

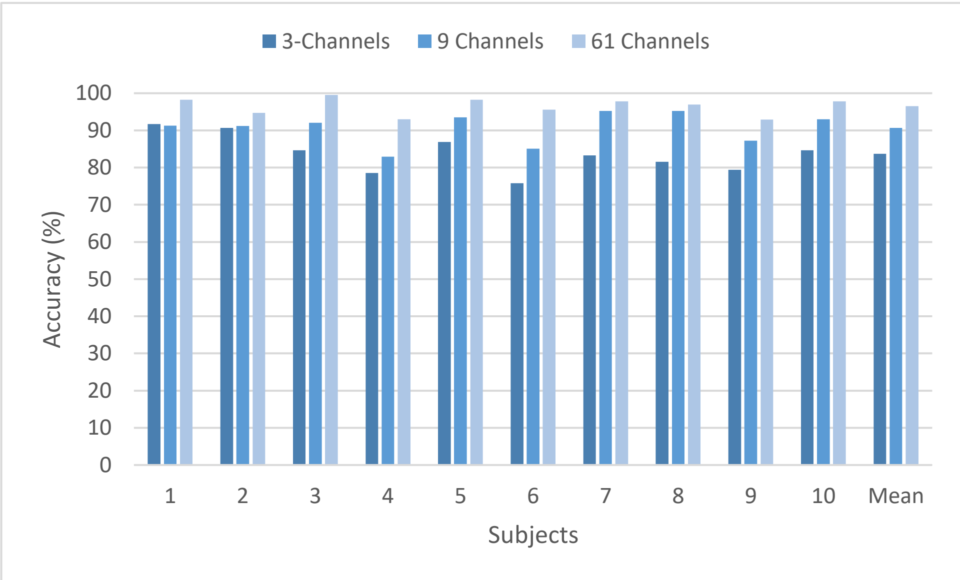
By using the cut-off frequencies at which the highest classification accuracy is obtained, the time interval when movement and resting states can best be distinguished from the MRCP signals is examined. For this purpose, classifier performances were investigated using EEG signals at three different time intervals covering pre-stimulus 2s (BP), post-stimulus 1s (MMP), pre-stimulus 2s, and post-stimulus 1s time intervals (BP and MMP), respectively. The classification accuracy rates for 10 subjects at three different time intervals selected are shown in Figure 6. According to the Figure 6. a, it was determined as 94.69% when the movement and resting states were determined using the 2s time window before the stimulus, 94.85% when the stimulus was determined using the 1s time window after the stimulus, and 96.47% when both the stimulus and post-stimulus time intervals were used together. Thus, only the pre-stimulus time window can be used to determine the movement state with high accuracy; however, using the pre-stimulus and the post-stimulus time windows together also increases the classification accuracy. This situation offers important information, especially for real-time applications and analysis of continuous movements. In Figure the 6. b, the confusion matrices for all three time intervals are given. According to the Figure 6.b, both movement and resting states were determined with an accuracy above 93%. The best accuracy of determining the movement and resting states for the [-2 1] time interval was determined as 97.15% and 95%, respectively.

The effect of the number of channels on system performance was investigated by using the best performing frequency band and time window. For this purpose, three different channel combinations given in Table 1 were chosen considering the literature. Channel combination 1 contains electrodes C3, Cz, and C4 located at the central point. Channel combination 2 includes a total of nine channels from the frontal, parietal, and central regions. Channel combination 3 contains all the electrodes in the dataset.

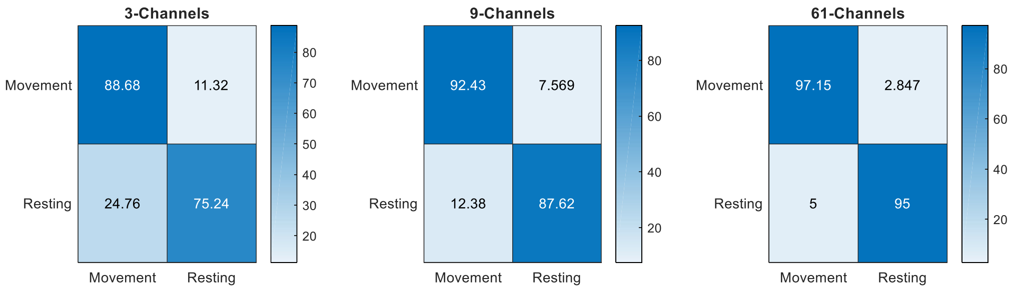
Table 1. *Channel combinations*

Channel Combination	*Number of Electrodes*	*Positions of Electrodes*
1	*3*	*C3, Cz, C4*
2	*9*	*F3, Fz, F4, C3, Cz, C4, P3, Pz, P4*
3	*61*	*All electrodes in the dataset [24]*

In the experiments for the three-channel combination, the filter cutoff frequency was 0.3–50 Hz and the time window was chosen to cover the 2s before the stimulus and 1s after the stimulus, as the highest classification accuracies were obtained in the previous experiments. The classification accuracies and confusion matrices obtained for three different channel combinations are shown in Figure 7. According to Figure 7. a, the average classification accuracies for 3, 9, and 61 channels were determined as 83.71%, 90.67%, and 96.47, respectively. According to the experimental results, the highest classification accuracy was obtained when all electrodes were used. However, with different signal processing and classification techniques, movement detection accuracy can be enhanced even if 9 channels are used. When the confusion matrices are examined, the movement state accuracies for 3, 9, and 61 channels are 88.68%, 92.42%, and 97.15%, respectively, and the resting state accuracies are 75.24%, 87.62%, and 95%, respectively. Thus, it is seen that the movement state is determined with higher accuracy for all three channel combinations.



(a)



(b)

Figure 7. *(a) Classification accuracies (b) Confusion matrices for 3, 9, and 61 channels*

4. DISCUSSION

Especially in real-time BCI systems, to design of self-paced systems, it is important to be able to determine the movement intentions of the users before the movement onset. In order to determine the user's movement intention, it is necessary to distinguish between the movement and resting states. Because MRCPs occur related to the movement intention before the movement onset, they can be used to differentiate the movement and resting states. The detection of the MRCP signal, which is an important sign that the movement will begin before the movement, has been discussed in several studies. However, no consensus could be reached regarding the preprocessing steps. In this study, we discussed the effect of preprocessing steps on the detection accuracy of the MRCP signal. The accuracy, sensitivity and specificity values of the classifier are summarized for the time window length, number of channels and cutoff frequencies examined in Table 2. According to the results, it is observed that MRCP signals can be detected with the highest classification accuracy in the case of using 61 channels and 0.3-50Hz band-pass filter in a window interval covering 2s pre-movement and 1 second post-movement duration.

When we examine the results in terms of the time window, it is seen that the accuracy rate is 94.69% in case only the pre-stimulus time window is used. These results indicate that the planning stage (BP) of MRCP includes important information related to the movement onset. However, by extending the time window by 1 s to include the post-movement time window, the MRCP detection accuracy is improved. On the other hand, the number of channels used in BCI systems is one of the important factors affecting the system cost. Besides, the number of channels used increases the processing costs in terms of the number of features and classifier complexity. Therefore, in BCI systems, it is an important expectation to achieve the highest classification accuracies using minimum channels. In this study, although 90.67% accuracy could be obtained with 9 channels, the accuracies obtained with three channels were limited to 83.71%. Therefore, classifier accuracies need to be improved in case few channels are used.

In BCI systems, detection of movement intention using MRCP signals has been discussed, in several studies in the literature. In Table 3, in order to evaluate the performance of the proposed method, the results obtained in the study are compared with studies in the literature. Upper limb movements datasets collected by Ofner et. al. are employed in several studies to determine the movement intention. In these studies, various signal processing and classification techniques were used together with different preprocessing steps. Mammone et al. [37] used 61 channels and the 1-s window preceding movement onset, while Duan et al. [17] employed eleven channels and [-2 0] time window, and they achieved approximately 90% classification accuracy. On the other hand, Chu et al. [18] collected their own dataset, which includes EEG signals during MI. They used 8–15 Hz BPF and 64 channels at the pre-processing stage and achieved 80.49 classification accuracy for movement/resting states. Ieracitano et al [19] employed CNN to distinguish

Table 2. *The effect of the length of the signal window to be examined, the number of channels and the cutoff frequency on the system performance according to the 0s point where the stimulus is given*

		Accuracy	***Sensitivity***	***Specificity***
Window length	***[-2 0] s***	*94.69*	*94.24*	*94.28*
	[0 1] s	*94.85*	*93.80*	*95.88*
	[-2 1] s	*96.47*	*97.15*	*95.31*
Number of channels	***3 channels***	*83.71*	*88.67*	*75.09*
	9 channels	*90.67*	*92.44*	*87.62*
	61 channels	*96.47*	*97.15*	*95.31*
Cut-off frequency	***0.3–5 Hz***	*81.80*	*87.24*	*72.48*
	0.3–10 Hz	*88.25*	*90.63*	*84.18*
	0.3–25 Hz	*93.85*	*95.03*	*91.77*
	0.3–50 Hz	*96.47*	*97.15*	*95.31*

movement/resting states using the same dataset used in this study. They achieved 90.50% accuracy to distinguish hand open movement and resting states by using 61 channels and 1-s time window preceding movement onset. As it can be seen from the Table 3, there is no consensus among the preprocessing steps in the literature. In this study, the 96.47% classification accuracy is achieved by using KFD and SVM in case of using 0.3-50 Hz BPF, [-2 1] time window and 61 EEG channels. This study also provides important results in terms of evaluating the effect of preprocessing steps on MRCP detection accuracy by using the same feature extraction and classification method for all experimental cases.

Table 3. *Comparison of the results of the studies with the literature*

Study	***Methodology***	***Dataset***	***Preprocessing***	***Accuracy (%)***
Ofneret.al. [16]	*Shrinkage regularized linear discriminant analysis (sLDA) classifier embedded in the discriminative spatial pattern (DSP)*	*ME and MI dataset collected by Ofner et. al.*	*Removing the noisy channels* *0.3 Hz—3 Hz BPF*	*85.5 (ME dataset)* *73 (MI dataset)*
Chu et al.[18]	*Riemannian geometry+PLS-based feature selection +LDA*	*MI dataset collected by Chu et al.*	• *8–15 Hz BPF* • *The 1-s overlapped window* • *64 channels*	*80.49 (movement/resting for average six movement classes)*
Duan et al. [17]	*Task-related component analysis and canonical correlation patterns*	*ME and MI dataset collected by Ofner et al.*	• *4Hz and 40 Hz BPF* • *11 electrodes (FCz, C3, Cz, C4, CPz, F3, Fz, F4, P3, Pz, P4)* • *[-2 0] time window*	*90.01 (movement/resting for average six movement classes)*
Mammone et al. [37]	*Continuous Wavelet Transform (CWT) based time-frequency mapping +CNN*	*ME and MI dataset collected by Ofner et al.*	• *the 1-s window preceding movement onset* • *61 channels*	*90.30*
Ieracitano et al. [19]	*CNN*	*Attempted hand and arm movement dataset*	• *61 Channels* • *1-s window preceding movement onset*	*89.65 (Hand-close/Resting)* *90.50 (Hand-open/Resting)*
This study	*KFD+SVM*	*Attempted hand and arm movement dataset*	*0.3-50Hz BPF* *61 Channels* *[-2 1] s time window*	*96.47%*

6. CONCLUSION

Since MRCPs contain important information about the start of the movement before the movement onset, robust analysis of the movement intention is of critical importance, especially for designing movement-related BCI systems and self-paced BCI systems. High-accuracy resolution of single-trial MRCPs before and during the movement is important in terms of providing real-time control of BCI systems and turning these systems into reliable and efficient systems in practice. In this study, it was aimed to determine MRCPs from single trial EEG signals and thus to classify movement and resting states with high accuracy. The results of the study show that the movement and resting states of MRCPs can be classified with 96.47% accuracy by using KFD and non-linear SVM methods. The highest classification accuracy was achieved using time windows including before and after the stimulus, the EEG signals recorded from 61 electrodes, and a filter with a cutoff frequency of 0.3–50 Hz.

The estimation of movement at the planning stage is an important piece of information for BCI systems. However, if the time window to be examined is increased to include the post-movement time, the high accuracy rates obtained can be used as an important control parameter, especially in BCI systems designed using continuous commands. Moreover, the experimental results show that MRCPs can be determined using the three channels; however, the classification accuracy needs to be improved in order to achieve higher accuracy if fewer channels are used.

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