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Improving Pre-movement Pattern Detection with Filter Bank Selection

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Abstract.

Objective: Pre-movement decoding plays an important role in detecting the onsets of actions using low-frequency electroencephalography (EEG) signals before the movement of an upper limb. In this work, a binary classification method is proposed between two different states.

Approach: The proposed method, referred to as filter bank standard task-related component analysis (FBTRCA), is to incorporate filter bank selection into the standard task-related component analysis (STRCA) method. In FBTRCA, the EEG signals are first divided into multiple sub-bands which start at specific fixed frequencies and end frequencies that follow in an arithmetic sequence. The STRCA method is then applied to the EEG signals in these bands to extract canonical correlation patterns. The minimum redundancy maximum relevance feature selection method is used to select essential features from these correlation patterns in all sub-bands. Finally, the selected features are classified using the binary support vector machine classifier. A convolutional neural network (CNN) is an alternative approach to select canonical correlation patterns.

Results: Three methods were evaluated using EEG signals in the time window from two seconds before the movement onset to one second after the movement onset. In the binary classification between a movement state and the resting state, the FBTRCA achieved an average accuracy of 0.8968±0.0847 while the accuracies of STRCA and CNN were 0.8228±0.1149 and 0.8828±0.0917, respectively. In the binary classification between two actions, the accuracies of STRCA, CNN, and FBTRCA were 0.6611±0.1432, 0.6993±0.1271, 0.7178±0.1274, respectively. Feature selection using filter banks, as in FBTRCA, produces comparable results to STRCA.

Significance: The proposed method provides a way to select filter banks in pre-movement decoding, and thus it improves the classification performance. The improved pre-movement decoding of single upper limb movements is expected to provide people with severe motor disabilities with a more natural, non-invasive control of their external devices.

Keywords: Brain Computer Interface, Movement Detection, Pre-movement Decoding, Standard Task-Related Component Analysis, Filter Bank Selection

1. Introduction

Movements of the human limbs lead to potential changes on the human scalp, which can be observed with non-invasive brain-computer interface-based electroencephalography (EEG) signals [1,2]. In previous studies on movement detection with EEG signals, motor imagery (MI) is one of the most frequently used brain activities in the motor cortex [3–5]. When the limbs begin moving, the power of EEG signals in alpha rhythm (frequency range: 8∼12 Hz) and beta rhythm (frequency range: 13∼30 Hz) shows an upward or downward trend, which is called event-related desynchronization/synchronization [6]. When humans imagine a movement of the left or right limb, the power changes in the left/right half of the scalp. However, these power changes in MI occur after the limb moves, which implies that in MI analysis movement can only be detected after the onset of the imagined movement [6]. Looking at the brain activity through the movement-related cortical potential (MRCP), the movement of human limbs or the resting state before the movement onset can be evaluated. Hence, MRCP is expected to help enhance the restoration of useful motor functions and reduce the time delay of movement detection [7, 8].

MRCP is a type of low-frequency EEG signal (frequency range: 0.5∼10 Hz) acquired in the motor cortex [9–11]. MRCP analysis is applied to EEG signals located around the movement onset. The readiness potential (RP) section is the stage that starts from 2 seconds before the onset and ends on the onset [12], while the movement monitoring potential (MMP) section is the stage that starts on the onset and ends 1 second after that [12]. The pre-movement patterns decoded from the RP section in MRCP signals cannot be observed directly. Grand average MRCP is a way to visualize the pre-movement patterns (Figure 1). In grand average MRCP, EEG signals acquired from the motor cortex are averaged across trials. The grand average MRCP of the upper limb movement shows an increase followed by a rapid decrease around the onset compared to the relatively steady grand average MRCP of the resting state. The pre-movement patterns are the features extracted from the RP section based on the grand average MRCP [13, 14].

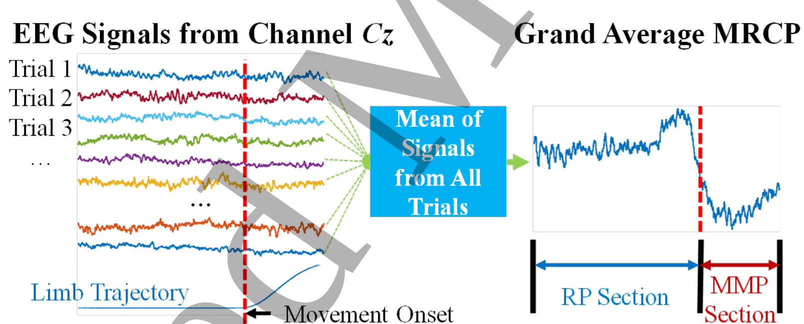


Figure 1. The concept of grand average MRCP. Multiple trials are obtained for MRCP analysis in the EEG paradigm by repeating the same limb movement. Therefore, EEG signals have three dimensions (channel, time and trial). Since the grand average MRCP is obtained by averaging all the trials, it has two dimensions (channel and time). In this figure, channel C_z is used as an example. The movement onset is the onset of the action when the limb begins to move. The grand average MRCP of the action shows an increase followed by a decrease around the movement onset.

By analyzing the grand average MRCP, some previous works focused on the binary classification between a movement state and the resting state or the binary classification between two actions. For instance, Jeong *et al.* proposed the subject-dependent and section-wise spectral filtering method (SSSF) to extract the amplitude features in MRCP and successfully solved the two-class problem between movement and resting states [15]. This method uses the mean amplitude of MRCP signals in both RP and MMP sections as the features. To optimize the selected features, Jeong *et al.* adopted a cross-validation and testing method to select the best frequency range for each subject. Ofner *et al.* proposed the discriminative spatial pattern method (DSP) [16], which calculates a linear discriminant analysis classifier for every time step. It was shown that the accuracy increases as the time point approaches the onset of the action in both the RP and MMP sections. Mammone *et al.* proposed the deep convolutional neural network (DCNN) [14], which decodes pre-movement patterns from time-frequency maps of EEG signals at the source level. Duan *et al.* proposed a pre-movement pattern decoding method, the standard task-related component analysis (STRCA) [13] consisting of the task-related component analysis (TRCA) spatial filter and the canonical correlation pattern (CCPs) features. All the methods mentioned above, except for the subject-dependent and section-wise spectral filtering method, are also a solution to the binary classification between two actions. In Table 1, the binary classification results of each method are given.

Table 1. Binary Classification Results in Pre-movement Decoding

Method	Movement vs Resting	Movement vs Movement
STRCA [13]	0.8287±0.1101	0.5970±0.1424
DCNN [14]	0.9030±0.0560	0.6247±0.0070
SSSF [15]	0.7300±0.0783	-
DSP [16]	0.8500±0.0500	0.4400±0.0700

Although STRCA has a very concise structure, it faces the frequency range selection problem when decoding pre-movement patterns in MRCP analysis. In both the SSSF and DCNN methods, the frequency characteristics of the EEG signals is considered when optimizing the two classification methods. The frequency characteristics are optimized by either using filter bank selection with cross-validation and testing or by constructing a time-frequency map [14,15]. Considering this, it can be seen that STRCA could be further improved with the filter bank technique.

Filter bank selection aims to solve the feature selection problem among various sub-bands in the frequency domain. It is widely used to analyze brain activity such as in MI and in steady-state visually evoked potential (SSVEP). In SSVEP analysis, the canonical correlation analysis method is a classical method used for detecting stimulus frequencies [17]. Canonical correlation analysis can measure the similarity between EEG signals and the reference signals, and many methods in SSVEP analysis have been developed based on this technique [18–20]. Filter bank canonical correlation analysis was proposed to incorporate harmonic and fundamental frequency components, which improved the detection of standard canonical correlation analysis in SSVEP [21]. Without the filter bank technique, the canonical correlation analysis faces the problem of selecting frequency components. In MI analysis, the common spatial pattern method is the most classical one [22]. The method extracts the logarithm-variance features from the EEG signals filtered by the spatial filter, and it shows a varying accuracy among the sub-bands in alpha (8∼12 Hz) and beta (13∼30 Hz) rhythms [3,23]. Filter bank common spatial pattern is an advanced MI analysis method that was developed by combining the common spatial pattern method and the filter bank technique [24]. The method is able to avoid sub-band selection, thus achieving better and more stable accuracies than the common spatial pattern method.

In both MI and SSVEP analysis, the filter bank technique uses a feature selection method to optimize the extracted common spatial pattern features or the canonical correlation features in each sub-band. The optimal frequency range of the filter bank varies among the subjects due to individual differences. The feature selection method overcomes the frequency range selection problem and enables the classification to achieve a stable and accurate result. When applying the filter bank technique to STRCA, there are three problems to tackle:

(1) The frequency range setting is unknown, so it is unclear how the starting and stopping frequencies of the sub-bands in the filter bank technique can be selected;
(2) The feature selection method for STRCA is undetermined;
(3) The feature arrangement is unclear when applying the feature selection method on STRCA features extracted from all sub-bands.

This study aims to analyze how to incorporate the filter bank technique into STRCA. Two steps are adopted for the improvement of the STRCA method in this work: firstly, three feature range settings are compared to decide how to select the frequency range of each sub-band in pre-movement decoding; secondly, a new filter bank TRCA (FBTRCA) method is proposed to decode the pre-movement patterns for the binary classification between a movement state and the resting state or between two actions.

FBTRCA consists of four steps: frequency bank division, spatial filtering, feature selection and classification. In the first step, the EEG signals are bandpassed into multiple sub-bands in the low-frequency domain. In the second step, canonical correlations are extracted from each of these sub-bands by the STRCA method. In the third stage, a feature selection algorithm is used to select the essential features from the features of all bands automatically. In the fourth step, a classifier is used to classify the selected features. This paper presents a selection of feature selection methods and classifiers for use in FBTRCA, and recommends suitable feature selection and classifiers for MRCP-based brain-computer interface.

In Section 2, the EEG dataset and the data pre-processing mechanism used are introduced, and the proposed FBTRCA method is described. In Section 3, the proposed method is analysed in terms of the frequency range settings, the feature selection and when compared to other methods. In Section 4, the FBTRCA design and workings in pre-movement decoding is discussed. Finally, Section 5 contains the conclusions for this study.

To facilitate the understanding of the contents in this work, the abbreviations are given in Table 2.

Table 2. Descriptions of Abbreviations

Abbreviation	Full Name	Description
EEG	Electroencephalograph	Multi-channel signals acquired from the surface of brain scalp.
MRCP	Movement-Related Cortical Potential	A kind of brain activity related to pre-movement.
MI	Motor Imagery	A kind of brain activity related to movement.
SSVEP	Steady State Visual-Evoked Potential	A kind of brain activity evoked by visual stimulus.
RP	Readiness Potential	EEG signals in the two-second window before the movement onset.
MMP	Movement Monitoring Potential	EEG signals in the one-second window after the movement onset.
CCA	Canonical Correlation Analysis	A basic classification method in SSVEP [17].
FBCCA	Filter Bank Canonical Correlation Analysis	A method that optimizes CCA by filter bank selection [21].
CSP	Common Spatial Pattern	A basic classification method in MI [22].
FBCSP	Filter Bank Common Spatial Pattern	A method that optimizes CSP by filter bank selection [24].
SSSF	Subject-dependent and section-wise spectral filtering	A binary classification method for movement and resting states [15].
STRCA	Standard Task-Related Component Analysis	A binary classification method for movement and resting states [13].
FBTRCA	Filter Bank Tasked-Related Component Analysis	The method that optimizes STRCA by filter bank selection.
TRCA	Task-Related Component Analysis	The spatial filter used in STRCA [13].
CCP	Canonical Correlation Pattern	The extracted features in STRCA [13].
CNN	Convolutional Neural Network	A feature selection method consists of convolutional layers.
MIQ	Mutual Information Quotient	A feature selection method based on mutual information [25].
MAXREL	Maximum Relevance	A feature selection method based on mutual information [26].
MINRED	Minimum Redundancy	A feature selection method based on mutual information [26].
MRMR	Minimum Redundancy Maximum Relevance	A feature selection method based on mutual information [26].
QPFS	Quadratic Programming Feature Selection	A feature selection method based on mutual information [27].
CIFE	Conditional Infomax Feature Extraction	A feature selection method based on mutual information [28].
CMIM	Conditional Mutual Information Minimization	A feature selection method based on mutual information [29].
MRMTR	Maximum Relevance Minimum Total Redundancy	A feature selection method based on mutual information [30].
SVM	Support Vector Machine	A binary classifier
LDA	Linear Discriminant Analysis	A binary classifier
NN	Neural Network	A binary classifier

2. Material and Method

2.1. Dataset Description

There are two public datasets used in this work, namely dataset I and dataset II [16, 31] ‡. Both datasets follow an offline acquisition paradigm in which a trial lasts five seconds. At the start of a trial, the computer screen displays a cross and emits a beeping sound. The computer screen then shows a cue that indicates the required movement or resting two seconds later. When the cue occurs, the subjects implement movements or remain at rest.

The EEG signals are acquired from 11 channels with active electrodes. These channels are located around the motor cortex. According to the 10/20 international system, 5 out of the 11 electrodes are located at the centre of the motor cortex: FC_z, C_3, C_z, C_4, CP_z; while the remaining 6 electrodes are located surrounding the motor cortex: F_3, F_z, F_4, P_3, P_z, P_4. The EEG signals are filtered with an 8-order Chebyshev bandpass filter from 0.01 Hz to 200 Hz. The sample rate of the EEG signals is 512 Hz, and the signals are downsampled to 256 Hz considering the computational load. A notch filter at 50 Hz is applied to avoid the influence of power line interference.

There are two main differences between the two datasets.

Firstly, dataset I contains signals related to hand movement trajectories acquired using a glove sensor. The onsets of the actions can be located with the movement

‡ `http://bnci-horizon-2020.eu/database/data-sets`,
Dataset I : 25. Upper limb movement decoding from EEG (001-2017) [16];
Dataset II: 26. Attempted arm and hand movements in persons with spinal cord injury (001-2019) [31].

trajectories of the limb. Dataset II, on the other hand, does not contain information about limb movement trajectories.

Secondly, both datasets have different actions and number of subjects. Dataset I consists of 7 states with 15 subjects. These states include the resting state *rest* and 6 actions: *elbow flexion*, *elbow extension*, *supination*, *pronation*, *hand close* and *hand open*. For each action, 60 trials were acquired during the signal acquisition. Dataset II, on the other hand, consists of EEG signals from 9 subjects. Each subject was asked to implement 5 actions, including *supination*, *pronation*, *hand open*, *palmar grasp* and *lateral grasp*. Each action has 72 trials.

In dataset I, the onset can be located from the hand trajectory when the movement is executed. However, the onset cannot be located in dataset II. Therefore, different processing procedures were adopted in the two datasets.

2.1.1. Pre-processing in Dataset I The STRCA method has been evaluated on dataset I in previous studies [13]. Here, we adopt the same pre-processing procedure. In dataset I, the hand movement trajectory is used to locate the movement onsets of the actions. The 1-order difference of the trajectory is taken, and then the 1-order Savitzky-Golay finite impulse response smoothing filter is used to smooth the signals. The length of the time window in the smoothing filter is set to 31. The starting value of the trajectory is subtracted from the trajectory in each trial. The approximate range of the onsets of the actions is the three-second time window with a one-second delay after the cue.

The two motions related to elbow movement, which are *elbow flexion* and *elbow extension*, lead to an increase in the amplitude of the hand trajectory. The trajectory is first changed into the absolute value. The hand trajectories are normalized by dividing them by the maximal absolute value. The location where the normalized trajectory is larger than the threshold of 0.05 is regarded as the movement onset. In trials that contain heavy noise contamination, the onsets of these actions cannot be located, and therefore these are manually removed.

For the other four states, the approximate range of the onset shrinks to a two-second time window with a one-second delay after the cue. The hand trajectory has a lower amplitude and is heavily influenced by noise. In these trials, trajectories are first normalized by dividing them by the maximal absolute value of each trajectory. The function $f(x) = a * \exp(-(\frac{x-b}{c})^2) + d$ is used to fit the smoothed and normalized trajectories by tuning the parameters a, b, c, d. The symbol 'exp' denotes the exponential function. Trials that fulfil $a < 0.05, c > 100$ and $d > 10$ are rejected. The onsets of the actions are determined by a threshold criterion, as the bias d is removed from the fitted function $f(x)$ and the onset is set to the location where the value of $f(x)$ is larger than 0.1.

For the signals in the resting state, the amplitude of the hand trajectory is supposed to be steady and have a small variance. The trials are rejected if the variances of the trajectories are greater than the set threshold of 0.02. The trajectories in the resting state have no movement onset. A fake onset is set to 2.5 s following the beeping sounds.

In Table 3, the number of trials after eliminating the rejected ones is given. The number of trials of these motions is averaged among all trials in dataset I and is rounded to an integer in the table.

Table 3. Average Number of Trials Across Subjects After Trial Rejection

Motion	*elbow flexion*	*elbow extension*	*supination*	*pronation*	*hand close*	*hand open*	*resting*
Number	60	59	52	51	56	55	59

The EEG signals can be divided into the RP and MMP sections with the located onsets or fake onsets. The features extracted from the RP section are the pre-movement patterns. In dataset I, we analyze the classification in two cases. In the first case, the EEG signals are from the RP section, and the results are used to analyze the performance of the proposed method in pre-movement decoding. In the second case, the EEG signals are from the RP and MMP sections. In Figure 1, the grand average MRCP shows an increasing trend, so therefore we assume that the EEG signals from both RP and MMP sections may improve the performance compared to the EEG signals from only the RP section.

2.1.2. Pre-processing in Dataset II The onsets of the actions in dataset II cannot be located by movement trajectory. Here, we adopt the same processing procedure in motor imagery as in [32]. EEG signals are extracted from the two-second time window after the cue. The onset is located within this time window, but the precise location is unknown.

Dataset II has five trial-based actions. Compared to the resting state of dataset I, the EEG signals in the resting state are not trial-based. Subjects were asked to have a long-duration rest after acquiring the EEG signals of the actions. The resting state for dataset II is generated by dividing the long-duration resting-state EEG signals into multiple trials. Each trial lasts 2 seconds, and there are 72 trials for each subject in total.

The data obtained was denoted as $\boldsymbol{X} \in \mathbb{R}^{N_c \times N_s \times N_t}$ or $X(t) \in \mathbb{R}^{N_c \times N_t}, t = 1, ..., N_s$, where N_c is the EEG channel number, N_s is the sample time and N_t is the number of trials. Before the binary classification tasks, EEG signals were normalized by z-score normalization. When evaluating STRCA and the proposed FBTRCA methods with this dataset, 10-fold cross-validation was applied, and the classification performance was calculated as the mean of these 10 folds. The binary classification was implemented between two motions, *e.g. elbow flexion* vs *elbow extension* and *elbow flexion* vs *resting* in dataset I. Therefore, dataset I has 21 motion pairs, while dataset II has 15 motion pairs.

2.2. Filter Bank Task-Related Component Analysis

2.2.1. Standard Task-Related Component Analysis STRCA is used to classify the EEG signals between a movement state and the resting state with MRCP signals in the RP section [13]. The method consists of two components: (1) spatial filter TRCA and (2) CCP features. The extracted features are classified with the linear discriminated analysis (LDA) classifier. Figure 2 illustrates the structure of STRCA.

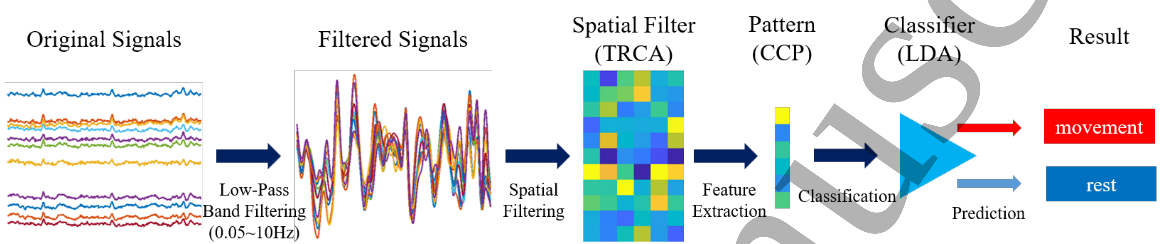


Figure 2. The structure of STRCA consists of the spatial filter TRCA and the extracted CCP features.

TRCA: The spatial filter of TRCA is designed by maximizing the reproducibility during the task [33]. In multichannel EEG signals, the training set is supposed to be $X^k(t) \in \mathbb{R}^{N_c \times N_t}$, where k refers to the class of the EEG signals, $k = 1, 2$. $X(t)$ consists of two kinds of signals: (1) task-related signals $s(t) \in \mathbb{R}$ and (2) task-unrelated noise $n(t) \in \mathbb{R}$. The relationship between $X(t)$, $s(t)$ and $n(t)$ is expressed by:

$$X_{i,j}^k(t) = a_{1,i,j}^k s(t) + a_{2,i,j}^k n(t),\ i = 1, ..., N_c,\ j = 1, ..., N_t. \tag{1}$$

$y(t)$ is the linear sum of EEG signals $X(t)$, and is defined as:

$$y_j^k(t) = \sum_{i=1}^{N_c} w_i^k X_{i,j}^k(t),\ j = 1, ..., N_t. \tag{2}$$

In TRCA, the task-related signal $s(t)$ is recovered from $y(t)$. The ideal solution is difficult to calculate but can be approached by maximizing the inter-trial covariance. The covariance C_{j_1,j_2}^k between the j_1-th trial and the j_2-th trial can be computed using:

$$C_{j_1,j_2}^k = Cov(y_{j_1}^k(t), y_{j_2}^k(t)) = \sum_{i_1,i_2}^{N_c} w_{i_1}^k w_{i_2}^k Cov(X_{i_1,j_1}^k(t), X_{i_2,j_2}^k(t)). \tag{3}$$

The covariances of all the trials are summed to obtain a combination of all trials:

$$\begin{aligned}\sum_{\substack{j_1,j_2=1\\ j_1\neq j_2}}^{N_t} C_{j_1,j_2}^k &= \sum_{\substack{j_1,j_2=1\\ j_1\neq j_2}}^{N_t} Cov(y_{j_1}^k(t), y_{j_2}^k(t)) \\ &= \sum_{\substack{j_1,j_2=1\\ j_1\neq j_2}}^{N_t} \sum_{i_1,i_2=1}^{N_c} w_{i_1}^k w_{i_2}^k Cov(X_{i_1,j_1}^k(t), X_{i_2,j_2}^k(t)) = \boldsymbol{w}^T S^k \boldsymbol{w}.\end{aligned} \tag{4}$$

To avoid infinite solutions of $\boldsymbol{w}$, the variance of $y_j^k(t)$ is constrained to 1:

$$\sum_{j_1,j_2=1}^{N_t} C_{j_1,j_2}^k = \sum_{j_1,j_2=1}^{N_t} Cov(y_{j_1}^k(t), y_{j_2}^k(t))$$
$$= \sum_{j_1,j_2=1}^{N_t} \sum_{i_1,i_2=1}^{N_c} w_{i_1}^k w_{i_2}^k Cov(X_{i_1,j_1}^k(t), X_{i_2,j_2}^k(t)) = \boldsymbol{w}^T Q^k \boldsymbol{w}. \tag{5}$$

The constrained spatial filter can be obtained by maximizing the generalized eigenvalue equation J, which is expressed as:

$$J = \frac{\boldsymbol{w}^T S^k \boldsymbol{w}}{\boldsymbol{w}^T Q^k \boldsymbol{w}}. \tag{6}$$

Eigenvectors are obtained by solving the generalized eigenvalue problem. The eigenvectors with the largest eigenvalues are selected as the eigenvectors that are to be used in the spatial filter. Three eigenvectors are adopted in TRCA. These eigenvectors from two classes are then combined into the TRCA spatial filter. The TRCA spatial filter that we obtained is $W \in \mathbb{R}^{N_c \times 6}$.

CCP: Using the training set of EEG data, $\boldsymbol{X}^k \in \mathbb{R}^{N_c \times N_s \times N_t}, k = 1, 2$, we can obtain the CCP templates $\hat{X}^k = \sum_{j=1}^{N_t} \boldsymbol{X}^k / N_t \in \mathbb{R}^{N_c \times N_s}, k = 1, 2$ for each of the two classes. The EEG signal of the trial from which we aim to extract features is $X \in \mathbb{R}^{N_c \times N_s}$. Given the TRCA spatial filter W, we extract the CCP after the EEG signals are transformed with W. Three kinds of correlation coefficients are considered in STRCA:

(1) Correlation coefficients between filtered signals:

$$X_k = \hat{X}^k; X_* = X; \tag{7}$$
$$\rho_{1,k} = corr(X_*^T W, X_k^T W), \ k = 1, 2; \tag{8}$$

(2) Correlation coefficients between filtered signals with a canonical correlation analysis projection:

$$X_k = \hat{X}^k; X_* = X; \tag{9}$$
$$[A_k, B_k] = cca(X_*^T W, X_k^T W) \tag{10}$$
$$\rho_{2,k} = corr(X_*^T W B_k, X_k^T W B_k), \ k = 1, 2; \tag{11}$$

(3) Correlation coefficients between the distances of filtered signals:

$$X_k = \hat{X}^k - \hat{X}^{3-k}; X_* = X - \hat{X}^{3-k}; \tag{12}$$
$$[A_k, B_k] = cca(X_*^T W, X_k^T W) \tag{13}$$
$$\rho_{3,k} = corr(X_*^T W A_k, X_k^T W A_k), \ k = 1, 2. \tag{14}$$

In the above equations, canonical correlation analysis is used to optimize the correlation between the templates $\hat{X}^k$ and X. The function symbols $corr$ and cca indicate the calculation process of the correlation coefficient and the process of CCA analysis, respectively. For each trial, we can obtain six features, which are referred to as CCP features in the following section.

2.2.2. Filter Bank TRCA This study proposes an FBTRCA method to enhance pattern decoding in MRCP analysis. Figure 3 shows the flowcharts of the proposed method, which consists of three major procedures: (1) filter bank analysis, (2) CCP feature extraction and (3) feature selection.

First, in the filter bank technique, the sub-bands are decomposed with multiple filters that have different pass-bands. In this study, the bandpass filter used for extracting sub-band components from the original EEG signals was an 8-order infinite impulse Butterworth filter.

STRCA is then applied to each sub-band separately, resulting in six CCP features. The number of sub-bands is denoted as m, such that the number of CCP features extracted from all sub-bands is $6\times m$=$6m$. The essential features are extracted from the $6m$ features in all sub-bands using one of the feature arrangement types. The feature arrangement type refers to the arrangement of the $6m$ CCP features when the feature selection method is applied.

Finally, the selected essential features are classified with the binary classifier. This study compares two classifiers, including the LDA and the support vector machine (SVM).

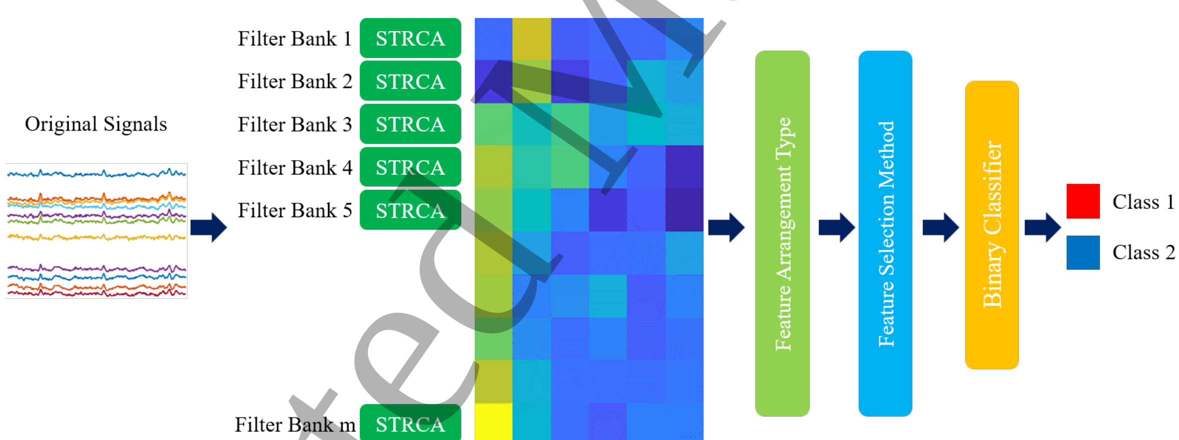


Figure 3. The structure of FBTRCA. CCP features are extracted from EEG signals using various filter banks, and a total of $6 \times m$ features are obtained. Then, feature selection methods are used to extract the essential features. A binary classifier is used to classify the selected essential features and predict the state of the EEG signals (movement or resting).

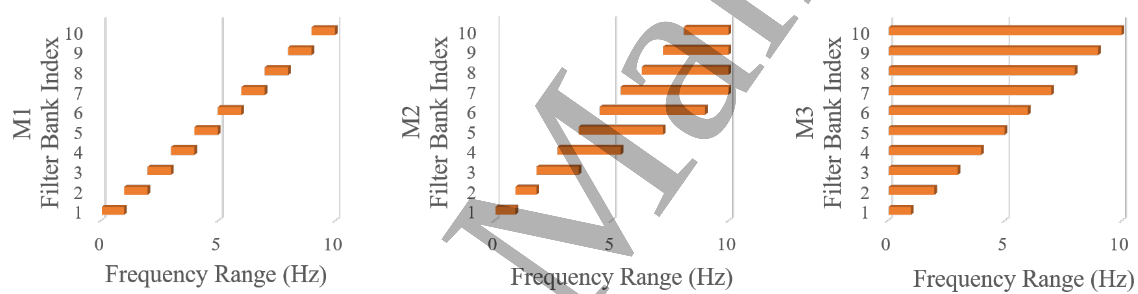
2.2.3. Frequency Range Settings In the decomposition of sub-bands, the decomposed EEG signals and classification accuracies vary with different frequency range settings of the filters. In the MI analysis, the frequency range of the filter banks was equipped with equally spaced bandwidths in alpha and beta rhythms, *e.g.* 4∼8 Hz, 8∼12 Hz, ..., 36∼40 Hz [32]. In the SSVEP analysis, the frequency range of the filter banks started at $n\times 8$ Hz and ended at a fixed frequency, *e.g.* 8∼88 Hz, 16∼88 Hz, ..., 80∼88 Hz, $n = 1, 2, ..., 10$ [21].

In MRCP analysis, the frequency range setting is undetermined. Considering that MRCP signals are a type of EEG signal with low frequencies, the maximum high cut-off frequency is set to 10 Hz. Three frequency arrangement settings are compared, including M_1, M_2 and M_3.

(1) M_1 Figure 4(a): The frequency range setting in M_1 is similar to that in FBCSP but with different low cut-off and high cut-off frequencies. The sub-bands in M_1 are equipped with equally spaced bandwidths.

(2) M_2 Figure 4(b): The frequency range setting in M_2 corresponds to the harmonic frequency bands. The high cut-off frequency is twice as high as the low cut-off frequency.

(3) M_3 Figure 4(c): The frequency range setting in M_3 is similar to the best setting in FBCCA. One of the two ends of the sub-bands is a fixed value. The low cut-off is fixed because the MRCP signals are in a low-frequency band. The high cut-off frequencies are arranged as an arithmetic sequence.



(a) M_1 (b) M_2 (c) M_3

Figure 4. Frequency range settings of sub-bands for the filter bank design. M_1: sub-bands with equally spaced bandwidths (*e.g.* 0.05 ∼1 Hz, 1∼2 Hz, ..., 9∼10 Hz).; M_2: sub-bands whose stopping frequency is twice as high as the starting frequency (*e.g.* 0.05∼0.9 Hz, 0.9∼1.8 Hz, 1.8∼3.6 Hz, ..., 8.1∼10 Hz).; M_3: sub-bands that start at a fixed frequency (*e.g.* 0.05∼1 Hz, 0.05∼2 Hz, ..., 0.05∼10 Hz). Considering that the MRCP are EEG signals with low frequencies, the maximum frequency of the range is set to 10Hz. In this figure, the number of filter banks is 10 (m=10).

2.2.4. Feature Arrangement Types From each of the sub-bands, six CCP features are extracted. The total number of features is therefore 6×m=6m. When selecting essential features from these using feature selection methods, there are two feature arrangement types that were used (Figure 5).

Type 1: The feature selection method is applied individually to each feature in the CCP. The feature selection method selects K1 essential features out of m features, and is applied six times. In the end, 6×K1 essential features are selected in total. The maximum value of K1 is 100.

Type 2: The feature selection method is applied to all six features in CCP simultaneously. The feature selection method is applied only once, and K2 essential features are selected from $6 \times m$ features. The maximum value of K2 is $6 \times m$ =600.

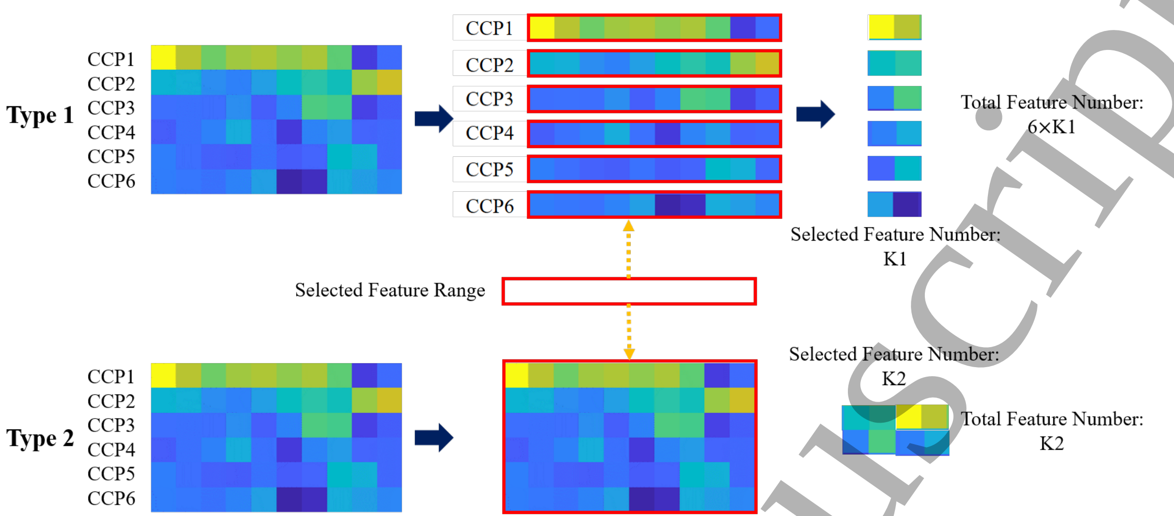


Figure 5. There are two arrangements that were used when selecting the features across these filter banks. Type 1: a feature selection method was applied to each feature in CCP respectively. Type 2: a feature selection method was applied to all six features in CCP simultaneously.

2.2.5. Feature Selection Methods Mutual-information-based approaches are a popular feature selection paradigm in data mining. In the FBCSP method of MI analysis, feature selection based on mutual information plays a significant role in optimizing the CSP features in all sub-bands. This study compares eight mutual-information-based feature selection methods to find a suitable one for selecting CCP features in multiple sub-bands. The compared feature selection methods include:

(1) Mutual Information Quotient (MIQ) [25]
(2) Maximum Relevance (MAXREL) [26]
(3) Minimum Redundancy (MINRED) [26]
(4) Minimum Redundancy Maximum Relevance (MRMR) [26]
(5) Quadratic Programming Feature Selection (QPFS) [27]
(6) Conditional Infomax Feature Extraction (CIFE) [28]
(7) Conditional Mutual Information Minimization (CMIM) [29]
(8) Maximum Relevance Minimum Total Redundancy (MRMTR) [30]

2.2.6. Binary Classifiers In STRCA, two binary classifiers have been compared, including the linear discriminate analysis (LDA) and the support vector machine (SVM). Because the number of features of STRCA is fixed, the simple LDA classifier shows the best performance among the three classifiers explored in [13]. In the proposed FBTRCA method, however, there are more than six features, and the number of features changes due to the feature selection settings. As a result, the kernel-based SVM classifier may show better performance when dealing with hyper-dimension features. Therefore, the two classifiers are also compared in this work.

2.3. Benchmark Method

The convolutional neural network (CNN) is used universally for feature selection. A neural network can be adjusted to an unknown function by backpropagation. The convolution unit in CNN can capture the local features of given inputs and thus select the essential features. Considering that the size of the EEG dataset is small, the CNN method with a simple architecture is used as the benchmark method for feature selection.

In the CNN architecture, the CCP features are the input of the neural network and are regarded as a 6-channel image. The height and width of the images are the numbers of the low cut-off frequencies and the high cut-off frequencies, respectively. A two-dimensional convolution layer is used to extract essential features from these CCP features. This convolution layer has 24 filters, each of size 3×3. A batch norm layer and a ReLu layer are used to normalize the output of the convolution layer. A 2×2 max pool layer with stride 2 follows the ReLu layer. Finally, a full-connect neural network with a hidden size of 50 is used as the binary classifier. The output of the hidden layer is normalized with the batch norm. The network is trained with an Adam optimizer with a learning rate of 0.001. The maximum training epoch is set to 200.

2.4. Performance Measurement

In binary classification, accuracy, F1-score and cross-entropy loss are three prevalent measurements for classification performance. In the classification task, the model will be tested after training. There are four outcomes in the testing result: true positive (TP), true negative (TN), false positive (FP) and false negative (FN) [34]. The definitions of these four outcomes for the binary classification are given as

TP = the number of cases is correctly identified as one class;
FP = the number of cases is incorrectly identified as one class;
TN = the number of cases is correctly identified as the other class;
FN = the number of cases is incorrectly identified as the other class.

The accuracy measures the ratio of the correctly predicted trials in the testing set, and is calculated through the following expression:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \tag{15}$$

In the calculation of F1-score, two measurements are considered: precision and recall. The precision is defined as

$$Precision = \frac{TP}{TP + FP}, \tag{16}$$

whereas the recall is defined as

$$Recall = \frac{TP}{TP + FN}. \tag{17}$$

F1-score is given by combining both precision and recall:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}. \tag{18}$$

Both the two classes have an F1-score, which are therefore denoted as $F1_1$ and $F1_2$. The macro-average F1-score (macroAVG) is used as a measurement which balances the F1-scores of the two classes:

$$macroAVG = 0.5 \times (F1_1 + F1_2). \tag{19}$$

Cross-entropy loss refers to the contrast between two random variables. It shows how accurate the classification model is by defining the difference between the estimated probability and the true label. The higher the difference between the two label outputs, the higher the loss. The cross-entropy loss is defined as

$$CrossEntropy = L(\boldsymbol{y}, \boldsymbol{t}) = -\sum_{k=1}^{2} \boldsymbol{t}_i ln(\boldsymbol{y}_i), \tag{20}$$

where $\boldsymbol{t}$ is the true label and $\boldsymbol{y}$ is the estimated probability. When measuring the classification performance of FBTRCA, the estimated probability is replaced with the predicated label of FBTRCA.

For the performance evaluation, 10-fold cross-validation is used. For each of the subjects and motion pairs, the accuracy, macroAVG and cross-entropy are averaged across 10 folds to get the mean and the deviation. When presenting the classification performance of the motion pairs, we average the means and the deviations of all the subjects. The final evaluation scores for each method are obtained by averaging the means and deviations across all subjects and motion pairs. We also use the two-side t-test to measure the improvement from STRCA to FBTRCA. The p-value is measured from the results of the 10 folds, for each of the subjects and motion pairs.

3. Results

The proposed FBTRCA method is evaluated with the two datasets. EEG signals are divided into the RP and MMP sections in the first dataset, while in the second dataset, the signals are in the two-second time window after the cue. The result analysis is carried out in three cases: when the EEG signals are from (1) the RP section in dataset I, (2) both the RP and MMP sections in dataset I, and (3) the two-second time window after the cue in dataset II. The performance of the classification methods is evaluated by 10-fold cross-validation.

This study aims to incorporate the filter bank technique into STRCA and thus propose a new methodology, FBTRCA. Three steps are necessary to achieve this goal:
(1) decide on the frequency range settings;
(2) evaluate the parameters K1 and K2 in the two types of feature arrangements;
(3) compare results achieved through FBTRCA against the benchmark.

In the first step, the properties of each filter bank will be determined, including the number of filter banks and their individual frequency ranges. The second step will evaluate K1 and K2 for each mutual-information-based feature selection method. The effects of LDA and SVM on FBTRCA are also compared in the second step. In the third step, the best performance of the FBTRCA method is compared to those achieved by the CNN and STRCA methods in the three cases presented above.

3.1. Analysis of the Frequency Range Settings

STRCA is applied to filter banks in three different settings: M_1, M_2 and M_3. Figure 6 shows the classification accuracies of each filter bank in the three settings. The performance is evaluated with the binary classification between the movement and resting states in the RP section of dataset I. The mean of the 6 (actions) $\times$ 15 (subjects) $\times$ 10 (folds) accuracies is taken to evaluate the classification performance.

In setting M_1, the accuracy decreases to 0.5 as the filter bank index increases. Similarly, the accuracy of the M_2 setting follows the same trend. The STRCA fails to solve the binary classification of the EEG signals in the sub-bands without low frequencies. Therefore, the two frequency range settings are not suitable for the combination of STRCA and the filter bank technique. In the M_3 setting, however, the accuracies in the filter banks are acceptable.

The main difference between M_3 and either M_1 or M_2 is that the frequency ranges of the filter banks in M_3 cover the sub-bands at low frequencies. The sub-bands at low frequencies maintain the information necessary for STRCA.

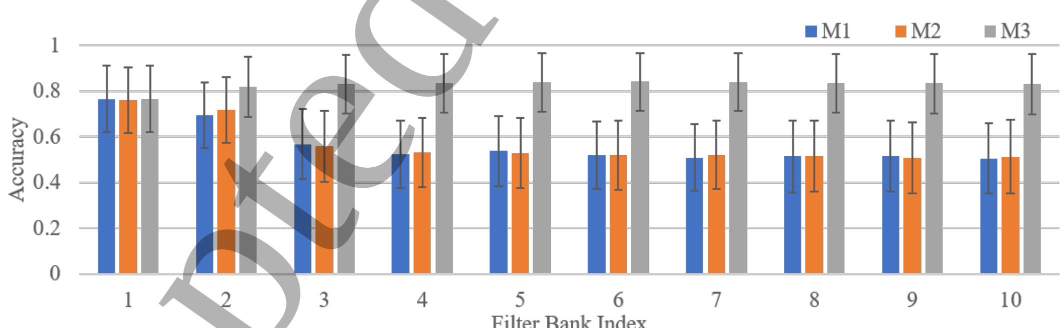
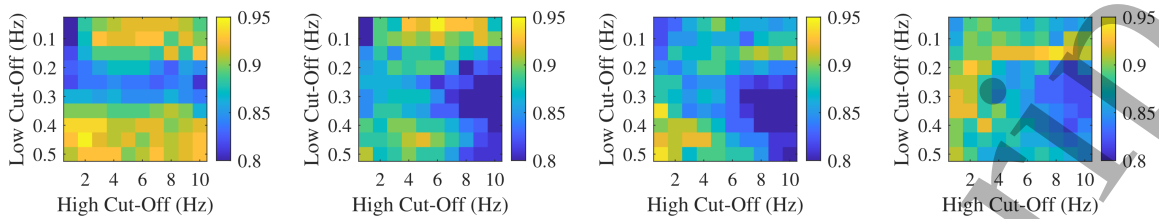


Figure 6. Classification accuracies of STRCA in three frequency range settings. In both the M_1 and M_2 settings, the accuracies decrease as the filter bank index increases, as the STRCA cannot tell the difference between the actions and the resting state. In the M_3 setting, the accuracy remains stable with an acceptable range. This means that M_3 is the only acceptable frequency arrangement setting among the three.

In the sight of these results, the M_3 frequency range setting is adopted with modifications in the design of the filter banks for the proposed FBTRCA method. The low cut-off frequency is shifted slightly from 0.5 Hz to 0.05 Hz with step 0.05 Hz, and the high cut-off frequency remains the same as that in $M3$. The total adopted number of sub-bands is 10×10.



(a) (b) (c) (d)

Figure 7. Average classification accuracies of STRCA in different sub-bands. (a) Subject 1, *elbow flexion* vs *resting* state; (b) Subject 1, *elbow extension* vs *resting*; (c) Subject 2, *elbow flexion* vs *resting*; (d) Subject 2, *elbow extension* vs *resting*. For different subjects or actions, the sub-band that has the best classification performance differs. Indeed, this is the reason why it is necessary to incorporate the filter bank technique in STRCA and develop the proposed FBTRCA method.

In Figure 7, the classification accuracies of STRCA in these sub-bands are given. The sub-bands with the highest accuracy vary for different subjects and actions. It is hard to decide on a suitable sub-band for STRCA, and for this reason, FBTRCA is proposed to solve this problem.

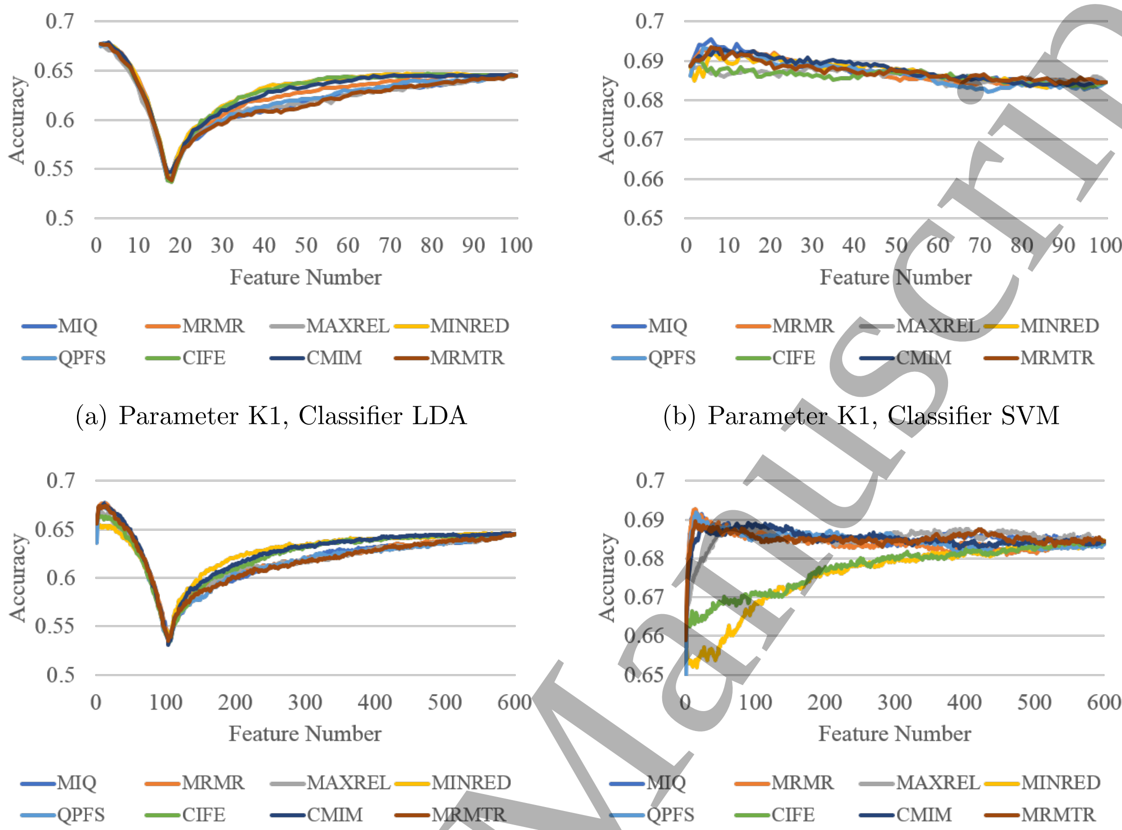
3.2. Analysis on Feature Selection Methods

After applying STRCA to 100 sub-bands, 6×100 CCP features are extracted. Then, feature selection methods select the essential features with a certain feature arrangement type. These essential features are classified with binary classifiers. In Figure 8, the classification performances of eight mutual-information-based feature selection methods are compared on two feature arrangement types. The essential features are classified with the LDA classifier and the SVM classifier (linear kernel). The statistics shown in Figure 8 are the average accuracies across subjects and motion pairs in the RP section of dataset I. The motion pairs include both (1) the binary classification between two actions and (2) the binary classification between a movement state and the resting state.

The results in Figure 8 are analyzed from three different perspectives: (1) binary classifiers, (2) comparison among the mutual-information-based feature selection methods, and (3) parameter searching on K1 and K2.

SVM and LDA are both basic binary classifiers used in machine learning. LDA casts the features into two classes through a linear projection, while SVM converts the features into hyper-space using a linear kernel and then casts the features in hyper-space into two classes. Because of the kernel, SVM is more efficient than LDA when tackling complicated features. In Figure 8, it can be seen that SVM has a better classification performance than LDA. The accuracies of LDA decrease sharply in Figure 8(a) and 8(c), and the best accuracy of LDA in Figure 8(a) is slightly lower than the accuracy of SVM in Figure 8(b). Therefore, the SVM classifier is better in the classification of FBTRCA.

In Figure 8, eight feature selection methods based on mutual information are



(a) Parameter K1, Classifier LDA

(b) Parameter K1, Classifier SVM

(c) Parameter K2, Classifier LDA

(d) Parameter K2, Classifier SVM

Figure 8. Tuning the K1 and K2 parameters with the LDA and SVM classifiers.

compared. These methods have similar accuracies except for MINRED (yellow line) and CIFE (green line). The accuracies of the other six methods have a similar (1) best accuracy and (2) changing trend. In the following analysis, the MRMR method is used as the feature selection method based on mutual information.

The ranges of K1 and K2 are 0∼100 and 0∼600, respectively. Despite their difference in range, their best accuracies are the same in Figure 8(b) and Figure 8(d). There is no significant difference between the two feature arrangement types when selecting essential features using methods based on mutual information.

To conclude on the above three points, the best procedure for the FBTRCA method has three steps. First, EEG signals are divided into 10×10 low-frequency banks according to the M_3 frequency range setting. Second, the feature selection method MRMR is used to select essential features. Finally, the selected essential features are classified using the SVM classifier. The number of selected essential features is about 15.

3.3. Comparison against Benchmarks

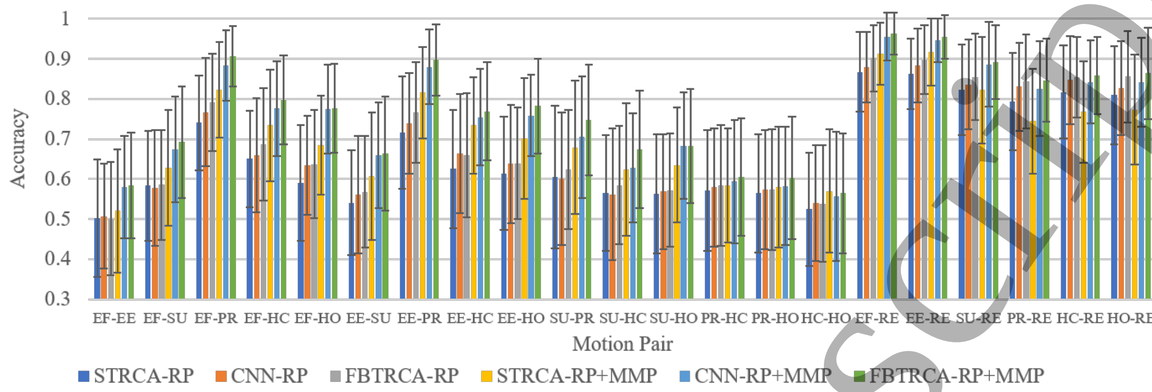
CNN is a universal feature selection method based on machine learning. The proposed FBTRCA method is compared against the STRCA and the CNN methods. The structure of the CNN model is given in Section 2.3. The input of the CNN method is $6 \times 10 \times 10$ CCP features, which include CCP features in 10×10 low-frequency filter banks. The input of the STRCA is the EEG signals in 0.05∼10 Hz.

A comparison between the STRCA, CNN and FBTRCA methods can be made using the accuracy, macroAVG and cross-entropy loss measurements, which are averaged across all subjects and all folds. In Figure 9, the results for the two cases in the dataset I are given, where the classification methods are applied to EEG signals in the RP section or to both the RP and MMP sections. The x-axis refers to the motion pairs, and the abbreviations are short for the names of actions. For example, 'EF' is short for '*elbow flexion*'. Figure 10 presents the classification results of dataset II. The classification methods are applied to the EEG signals in the two-second time window after the cue. Overall, it can be observed that the FBTRCA method outperforms the STRCA and CNN methods in both datasets. To better present the classification performance, we list the detailed accuracies for all subjects and motion pairs in the datasets I and II (Table 4-15). The detailed accuracies are results averaged from accuracies of ten folds of cross-validation. The mean and the deviation are listed in two separate tables.

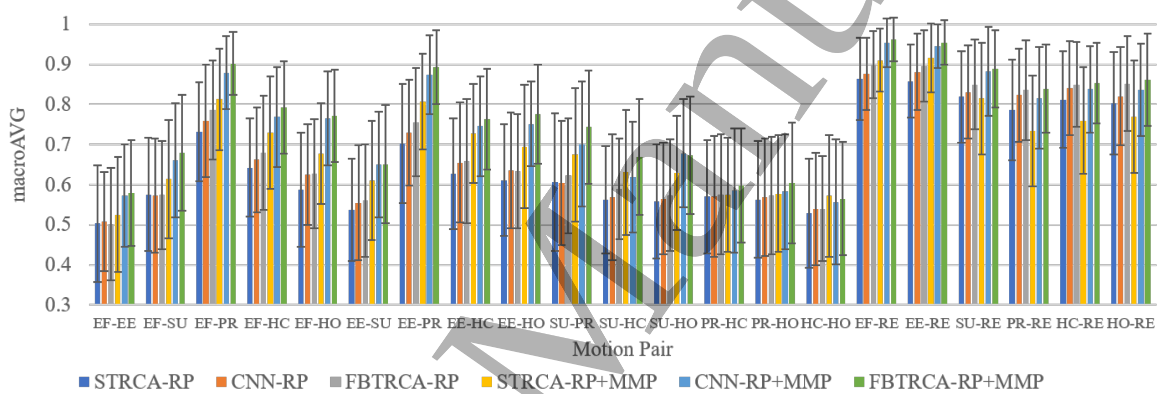
In dataset I, the binary classification is evaluated on the EEG signals in the RP section. The binary classification between actions and the resting state reflects whether the subjects want to move their limbs or stay at rest. The meaning of pre-movement decoding is to detect the movement intention before the limb moves. FBTRCA can improve the performance of pre-movement decoding compared to the previous STRCA method. When EEG signals in both RP and MMP sections are used, all three classification methods show an improved performance compared to the results for signals in only the RP section. The EEG signals are also different between the two states in the MMP section.

During the acquisition of EEG signals in dataset II, the limb movement trajectories were not recorded, and thus the onsets of actions cannot be located precisely. The two-second time window after the cue is taken in the classification evaluation. Within this time window, the subjects begin to move their limbs. Therefore, the two-second time window covers part of both the RP and MMP sections. Although the onsets cannot be located in dataset II, the FBTRCA still improves the classification performance.

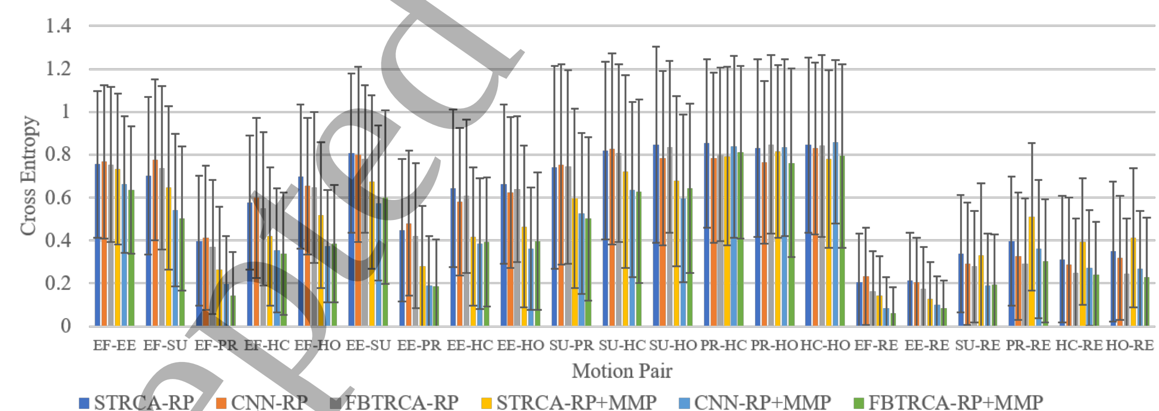
We also present the p-values of two-side t-test between the STRCA method and the FBTRCA method (Table 16-18). The p-values are calculated from the accuracies of ten folds, for each subject and each motion pair. In the three tables, the p-values are highlighted if the value is smaller than 0.1. In the dataset I (RP+MMP section), there is at least one subject that FBTRCA shows significant improvement than STRCA (p <0.1), except for the classification between *pronation* and *hand close* or between *pronation* and *hand open*.



(a) Dataset I, Accuracy

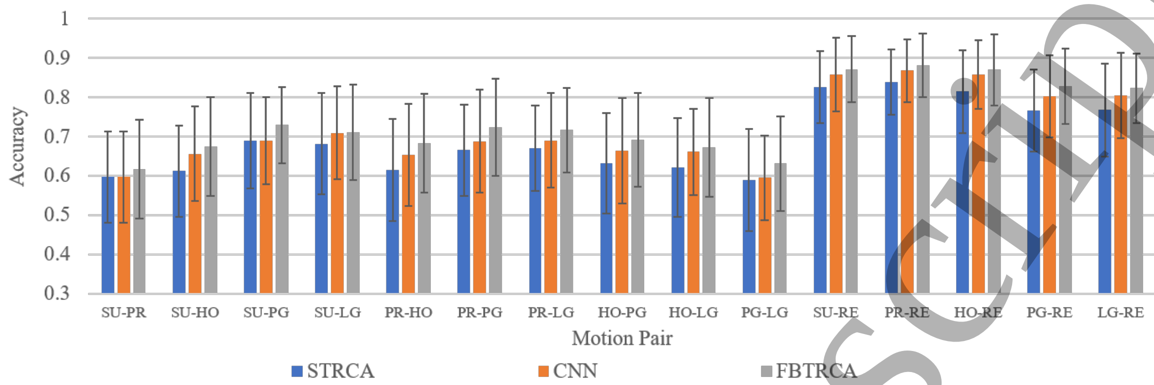


(b) Dataset I, MacroAVG

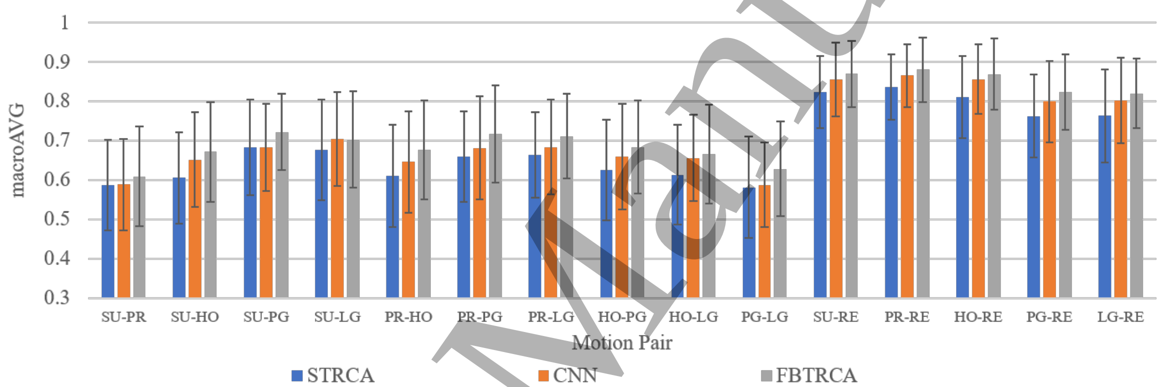


(c) Dataset I, Cross Entropy

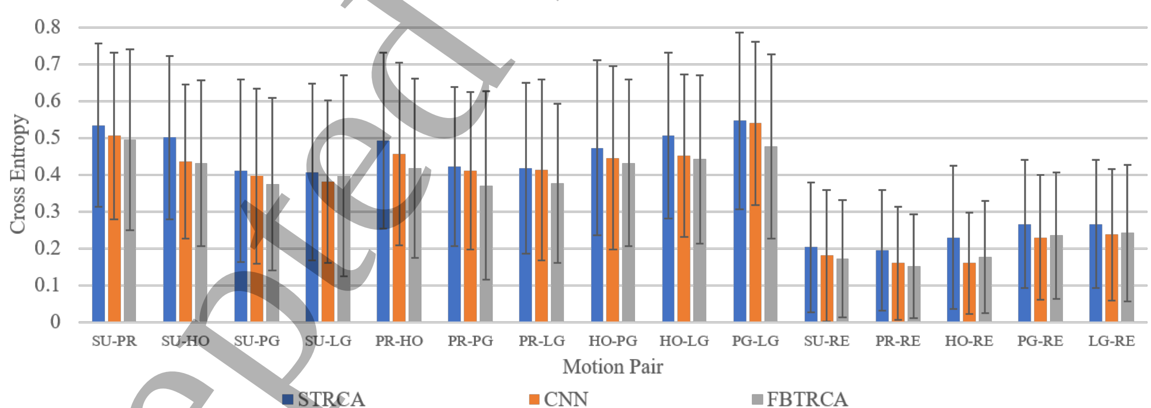
Figure 9. Accuracy, macroAVG and cross-entropy loss comparison in dataset I. Three methods including STRCA, CNN and FBTRCA are compared. The classification is evaluated in either the RP section or both the RP and MMP sections. The accuracies are averaged across all subjects and all folds. The x-label represents the motion pair in which the binary classification is applied. The abbreviations of these states are used in the figures to facilitate the presentation; for example, 'EF' is short for the movement state *elbow flexion*. Figure 9(a), Figure 9(b) and Figure 9(c) each refer to one of the three measurements respectively.



(a) Dataset II, Accuracy



(b) Dataset II, MacroAVG



(c) Dataset II, Cross Entropy

Figure 10. Accuracy, macroAVG and cross-entropy loss comparison in dataset II. Three methods including STRCA, CNN and FBTRCA are compared. The classification is evaluated in the two-second time window after the cue. The other settings of this figure are the same as those presented in Figure 9.

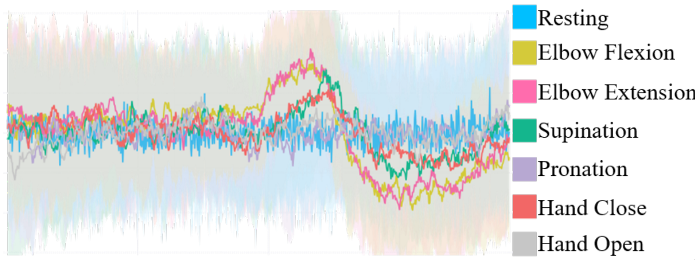


Figure 11. The grand average MRCPs of multiple motions.

In summary, the proposed FBTRCA method incorporates the filter bank technique into the basic STRCA method, thus presenting a comparable classification performance to STRCA in pre-movement decoding.

4. Discussion

In this study, we proposed a new pre-movement decoding method, FBTRCA. This method is developed by incorporating filter bank selection on the STRCA method. In comparison to MI signals, MRCP signals have the advantage that the movement patterns can be observed before the movement onset. FBTRCA is designed to extract features from the grand average MRCP, which contains information about the movement in MRCP signals. FBTRCA consists of three modules: the spatial filter TRCA, the CCPs features and the low-frequency bands. The associations between these and the grand average MRCP are detailed below. To better explain the relationship between FBTRCA and grand average MRCP, the grand average MRCP of multiple actions in channel C_z is presented in Figure 11.

The spatial filter is a linear transformation of multi-channel EEG signals. It plays the role of channel selection and thus optimizes the spatial characteristic of EEG signals. Our previous work pointed out that SSVEP and MRCP signals have similar spatial distributions, and the STRCA method was proposed by comparing the effects of different spatial filters for MRCP signals [13]. The spatial filter TRCA showed a better performance when compared to other spatial filters. Among the compared spatial filters, the discriminative canonical pattern matching is a spatial filter that maximizes the inter-class covariance and minimizes the intraclass covariance. However, even the performance of this filter was worse than TRCA. Therefore, the spatial filtering does not maximize the intraclass covariance in this work. As given in Section 2.2.1, TRCA searches for the projection matrix that maximizes the covariance of each trial in each class. The ideal spatial filter transforms the EEG signals of all trials into a single trial so that the covariances among these trials are maximized. The grand average MRCP is the mean of all the trials in each class. We assume that the ideal single trial is the grand average MRCP, although there might be some biases. The EEG signals of all the trials in each class approach the grand average MRCP of each class during the spatial filtering. Because the inter-trial noises are not correlated, the noise components in EEG signals have lower eigenvalues. The noises are removed from the signals by taking the eigenvectors of the three maximum eigenvalues in the spatial filtering.

In Figure 11, the grand average MRCPs of multiple motions are different. In the binary classification, the class of an EEG trial is determined by the distances between the EEG trial and the two grand average MRCPs. The goal is to quantify the relationship between the EEG signals of each trial and the grand average MRCPs of two classes after the spatial filtering. CCPs are in fact used to measure the similarity between EEG signals and the grand average MRCPs. In the calculation of CCPs, three types of correlation coefficients are used to measure the similarity between EEG signals and the grand average MRCPs; these include (1) the correlation between EEG signals and the grand average MRCP, (2) the canonical correlation between EEG signals and the grand average MRCP, and (3) the canonical correlation between two differences, including the difference between EEG signals and the grand average MRCP and the difference between two grand average MRCPs. Because the three coefficients are measuring the similarity between EEG signals and the grand average MRCP and there are two grand average MRCPs, the number of total CCP features is six.

However, because the differences between the two motions are reflected in their grand average MRCP signals, the similarity between their grand average MRCP signals limits their classification performance. For instance, the classification between *elbow flexion* and *resting* has a high accuracy, but the classification between *elbow flexion* and *elbow extension* achieves an unsatisfactory performance.

The grand average MRCP plays an important role in STRCA and FBTRCA. But the calculation procedure is simple, which is the same as the procedure of the CCP templates given in Section 2.2.1. In the training set, the EEG signals of each trial are labelled. The grand average MRCP can be established simply by averaging EEG trials belonging to the same class. Calculating the grand average MRCP with the training set and using the grand average MRCP as a template can be derived from [35–37]. Their grand average MRCP was extracted from the surrogate channel in the training set. In our work, the template is extracted from the channels in the motor cortex. The number of channels in the grand average MRCP is then minimized by the task-related component analysis.

When applying filter bank selection to STRCA, the EEG signals are divided into several frequency ranges. As shown in Figure 12(a), the low cut-offs of these frequency ranges are small, while the high cut-offs are sorted in an arithmetic sequence. In MRCP analysis, the grand average MRCP shows an increase followed by a decrease around the movement onset. The grand average MRCP is a low-frequency signal. Figure 12(b) illustrates the power spectrum of the grand average MRCP. As the frequency increases, the time window with high power (yellow part) becomes narrow. Therefore, it is necessary to maintain the low-frequency components, as then the increasing high cut-off of filter banks can introduce more subtle features. For example, in Figure 12(a), the 0.5$\sim$3 Hz component reflects how the grand average MRCP changes. As the high

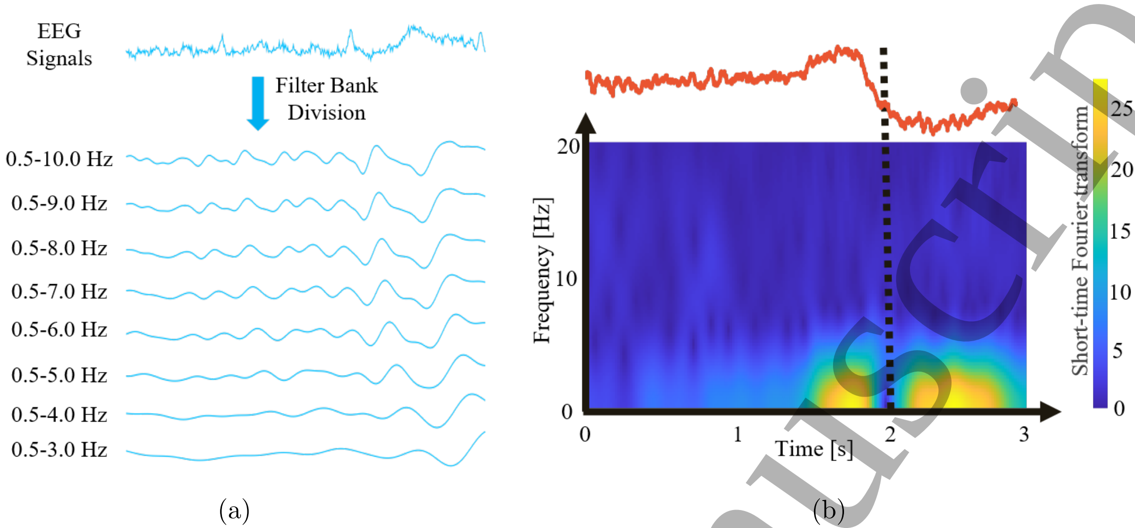


Figure 12. Frequency characteristics of MRCP signals. (a) Low-frequency components of MRCP signals in the RP section (M_3). (b) Power spectrum of the grand average MRCP in both RP and MMP sections, calculated by the short-time Fourier transform.

cut-off increases to 10 Hz, more local trends are introduced.

The Figure 12(a) can be used to explain why the frequency range setting M_3 is better than the other two settings. The correlation coefficients measure the similarity of the unlabeled trial and the grand average MRCPs. As mentioned above, the classification of STRCA and FBTRCA depends on the differences between two grand average MRCPs. The most discriminant features in the grand average MRCP are the increase and decrease around the movement onset (Figure 11). Reflected in Figure 12(a), the increase and decrease are located in the extremely low-frequency bands (0.5$\sim$3 Hz), which indicates the global trend of MRCP signals. When the high cut-off frequency increases, more subtle features are introduced. In the frequency range settings, M_1 and M_2, the global trend of MRCP signals is removed in the filtering and only subtle or local features are kept. It leads to the results that the increase and decrease trends are removed, and the differences of the increase and decrease between two motions cannot be further analyzed and distinguished in STRCA and FBTRCA. Therefore, the frequency range setting M_3 is used in the analysis of MRCP signals.

In the frequency range setting M_3 of Figure 4, the filter bank 10 (*e.g.*, 0.05$\sim$10 Hz) covers the ranges of the rest filter banks and thus contains the information from other frequency bands. However, the other filter banks are still important in the signal processing. This can be explained by the classification accuracies in multiple filter banks. In Figure 7, the average classification accuracies of multiple filter banks are presented. When the low cut-off of the filter bank is fixed to a small value, the accuracy of STRCA changes as the high cut-off frequency increases in an arithmetic sequence. The best accuracies among these bands are different among subjects and motion pairs. A possible reason is the influence of noise in the frequencies greater than the best frequency, and the insufficient information in the frequencies smaller than the best frequency. The best frequency bands cannot be determined directly by giving a certain frequency range. The filter bank selection across these frequency bands in the proposed FBTRCA is necessary when tackling this problem. Therefore, although the filter bank 10 covers all the other filter banks, the other filter banks are still necessary. The filter bank 10 may be influenced by undetected noises and is not in the best frequency range.

During the development of the FBTRCA method, the processing capabilities in SSVEP and MI are considered. This includes the canonical correlation coefficients in SSVEP and the feature selection on filter banks in MI.

SSVEP also uses canonical correlations as features for classification, but there are some differences. In SSVEP, there are two kinds of templates when calculating the correlation coefficients [33]. The first template is the CCP template averaged across trials in each class. The second template is the sinusoidal function. Because the visual stimulus in SSVEP has a specific frequency, the similarity between EEG signals and the sinusoidal function with a specific frequency can predict the frequencies of visual stimuli. Compared to SSVEP, MRCP has a natural drawback: the templates cannot be measured with frequencies. As shown in Figure 11, the differences between the grand average MRCPs of a motion pair are different. For example, the differences between the grand average MRCPs of *elbow flexion* and *elbow extension* is smaller compared to the differences between *elbow flexion* and *supination*. We cannot measure how much smaller the differences are, but they can be measured by the frequencies of visual stimuli in SSVEP. Therefore, it is difficult to classify the MRCP signals by adopting the maximum value of correlation coefficients as in SSVEP. The coefficients calculated in STRCA are used as features for further improvement by feature selection.

In Section 3, the classification results between EEG signals in the RP section and the RP+MMP sections are compared. The EEG signals in RP+MMP show an improvement over those in only the RP section. The reason is that the grand average MRCPs also show the differences between the two actions in the MMP section. Similarly to the result analysis of dataset II, it is not necessary to locate the onset of the action and divide the EEG signals into RP and MMP sections if one is only considering the classification of two classes. The classification results in the RP section indicate whether this method works in pre-movement decoding. The classification results in both the RP and MMP sections reflect the best classification performance that this method can achieve.

The feature selection methods we used are based on mutual information instead of similarity or sparse learning [38]. Mutual information is preferred in this case because it has shown to have good performances previously in FBCSP. Mutual information is also used in MI analysis when selecting features from filter banks. Because of the efficiency of mutual information in feature selection on filter banks, feature selection methods based on mutual information were first considered. Compared to feature selection with CNN, the feature selection based on mutual information achieved better performance, as shown in Figure 9. Compared to mutual information, sparse learning is suitable in the feature selection from both multiple filter banks and time windows [32].

Traditional EEG processing methods have three key points, spectral, spatial and temporal. The proposed FBTRCA method is associated with one point of the traditional method, spectral, *i.e.*, filter banking. According to our research experience on MRCP signals, FBTRCA and STRCA cannot well deal with the spatial optimization. The spatial filtering in STRCA and FBTRCA work as unrelated-components rejection. The introduce of more channels will lead to a decrease of the classification performance of STRCA and FBTRCA. The temporal characteristic used in FBTRCA and STRCA is the correlation, which measures the similarity of two time series. It can be further improved in future work. Besides, the STRCA and FBTRCA can only be used in the binary classification limiting to the scheme of STRCA. Migrating the two binary classification methods to the multi-class classification task is also an important work. In MRCP signals, the grand average MRCP is a special concept in EEG processing, which averages across all trials belonging to a class. However, averaging is a simple approach to finding the center points of all trials and inevitably introduces unexpected influences like outlier points. It is also possible to find a hyper-space that casts the trials to the discriminant points.

5. Conclusion

The proposed FBTRCA method incorporates the filter bank technique and solves the unstable accuracy problem. There are four steps in FBTRCA. First, EEG signals are divided into multiple sub-bands in the low-frequency domain. Second, CCP features are extracted from these sub-bands with the STRCA method. Then, the minimum redundancy maximum relevance method is used to optimize and select the CCP features. Finally, the selected features are classified with the SVM binary classifier. When decoding the pre-movement pattern in the RP and MMP section, the average accuracy increases from 0.8228 ± 0.1149 (STRCA) to 0.8968 ± 0.0847 (FBTRCA) in the binary classification between the actions and the resting state; the average accuracy increases from 0.6611 ± 0.1432 (STRCA) to 0.7178 ± 0.1274 (FBTRCA) in the binary classification between two actions.

6. Code availability

The code of this work is freely available here: `https://github.com/plustar/Movement-Related-Cortical-Potential`.

7. Acknowledgement

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Table 4. Mean of Classification Accuracies of Dataset I (RP) Across Ten Folds (Movement vs Movement)

Subject	Method	Motion Pair															Average
		EF-EE	EF-SU	EF-PR	EF-HC	EF-HO	EE-SU	EE-PR	EE-HC	EE-HO	SU-PR	SU-HC	SU-HO	PR-HC	PR-HO	HC-HO	
1	STRCA	0.5167	0.6000	0.7545	0.6364	0.5818	0.4400	0.6273	0.6091	0.4636	0.7333	0.6556	0.5333	0.5400	0.5600	0.5800	0.5888
	CNN	0.5083	0.6600	0.8636	0.6091	0.6545	0.6500	0.7455	0.5727	0.4636	0.6667	0.6222	0.5556	0.5400	0.5700	0.5200	0.6135
	FBTRCA	0.5333	0.6800	0.8455	0.7091	0.6182	0.6000	0.8000	0.5909	0.4818	0.7222	0.6667	0.6111	0.6000	0.5700	0.5200	**0.6366**
2	STRCA	0.5300	0.5700	0.7500	0.5500	0.4700	0.5600	0.7500	0.5100	0.4800	0.6800	0.5700	0.4600	0.6300	0.6300	0.5000	0.5760
	CNN	0.5300	0.5500	0.7900	0.4800	0.5000	0.5500	0.8000	0.5400	0.6100	0.7400	0.4900	0.5200	0.6100	0.5900	0.4800	0.5853
	FBTRCA	0.5700	0.5800	0.8400	0.5100	0.4800	0.6500	0.8300	0.4800	0.6200	0.7200	0.5500	0.5100	0.6100	0.6300	0.5000	**0.6053**
3	STRCA	0.4000	0.5700	0.7000	0.8455	0.7900	0.6900	0.6700	0.8909	0.7800	0.6000	0.6556	0.6125	0.6444	0.6500	0.6778	0.6784
	CNN	0.4250	0.6400	0.6900	0.8364	0.8200	0.6500	0.7000	0.8818	0.8200	0.5750	0.6111	0.6875	0.6222	0.5125	0.6556	0.6751
	FBTRCA	0.4583	0.5500	0.7700	0.8545	0.8400	0.6100	0.8100	0.9000	0.8400	0.5750	0.6778	0.6750	0.6444	0.6250	0.7000	**0.7020**
4	STRCA	0.4417	0.6000	0.8364	0.7750	0.6636	0.5000	0.8364	0.7250	0.7000	0.7600	0.6727	0.6500	0.5727	0.5900	0.5455	0.6579
	CNN	0.5667	0.5091	0.8636	0.7917	0.7273	0.5182	0.8636	0.7750	0.8091	0.7800	0.6727	0.7100	0.5727	0.5900	0.5455	0.6863
	FBTRCA	0.5500	0.4818	0.9182	0.8083	0.7545	0.5636	0.8545	0.8167	0.7818	0.8600	0.8091	0.7300	0.6000	0.6200	0.6182	**0.7178**
5	STRCA	0.6273	0.4727	0.7000	0.5727	0.4818	0.6000	0.7500	0.5800	0.6000	0.6600	0.5500	0.6000	0.6300	0.5300	0.5500	0.5936
	CNN	0.4636	0.5727	0.7091	0.5636	0.5818	0.5600	0.7100	0.6700	0.5700	0.5400	0.5700	0.5300	0.6000	0.6000	0.5700	0.5874
	FBTRCA	0.5091	0.5182	0.6909	0.5455	0.5909	0.6500	0.7200	0.6400	0.6200	0.5700	0.6000	0.5300	0.5900	0.6200	0.5200	**0.5943**
6	STRCA	0.5833	0.6545	0.9333	0.6636	0.8182	0.5000	0.8111	0.6000	0.7091	0.6000	0.5700	0.5800	0.5875	0.6000	0.6000	0.6540
	CNN	0.5167	0.6182	0.8667	0.6909	0.7818	0.5545	0.7889	0.6182	0.7455	0.5750	0.5800	0.5400	0.6625	0.6250	0.6200	0.6523
	FBTRCA	0.5083	0.7000	0.9222	0.7000	0.8091	0.5545	0.8000	0.6182	0.7273	0.5625	0.5400	0.5800	0.7000	0.5750	0.5900	**0.6591**
7	STRCA	0.5167	0.6000	0.7091	0.6182	0.5000	0.4545	0.7364	0.6364	0.6091	0.6900	0.5400	0.5300	0.5700	0.5400	0.5100	0.5840
	CNN	0.5500	0.5818	0.7091	0.5909	0.6182	0.5364	0.8000	0.6818	0.6182	0.6000	0.5200	0.5900	0.5600	0.5300	0.5200	0.6004
	FBTRCA	0.5500	0.6273	0.7727	0.6000	0.6182	0.5000	0.7818	0.6455	0.6636	0.6700	0.5100	0.5400	0.5300	0.5300	0.5300	**0.6046**
8	STRCA	0.5083	0.6455	0.7636	0.6364	0.6545	0.4818	0.7364	0.5364	0.5636	0.5400	0.5100	0.5800	0.5300	0.5200	0.4100	0.5744
	CNN	0.5083	0.6364	0.7818	0.6545	0.7000	0.5273	0.7000	0.6091	0.6000	0.4900	0.5400	0.4700	0.5500	0.4600	0.4400	0.5778
	FBTRCA	0.5250	0.6091	0.7818	0.6818	0.7000	0.5182	0.7727	0.6364	0.6818	0.5200	0.5200	0.5200	0.5600	0.4800	0.4500	**0.5971**
9	STRCA	0.5583	0.6545	0.7455	0.7000	0.5727	0.6000	0.6545	0.6182	0.6364	0.5000	0.4800	0.6500	0.4900	0.5800	0.4800	0.5947
	CNN	0.5000	0.6091	0.7273	0.6455	0.5545	0.5727	0.6909	0.6455	0.5455	0.4600	0.4900	0.5900	0.5900	0.7200	0.5200	0.5907
	FBTRCA	0.5667	0.6455	0.7545	0.7000	0.5727	0.5727	0.7091	0.6818	0.6182	0.5000	0.4600	0.6300	0.5100	0.6000	0.5000	**0.6014**
10	STRCA	0.4417	0.4273	0.5833	0.6909	0.4818	0.5091	0.6750	0.6636	0.5727	0.6273	0.5900	0.5300	0.5455	0.4909	0.5400	0.5579
	CNN	0.4250	0.4364	0.5750	0.7273	0.4545	0.5273	0.6333	0.7727	0.6364	0.6818	0.6400	0.6100	0.5273	0.4727	0.6400	**0.5840**
	FBTRCA	0.4583	0.4818	0.6083	0.7182	0.4455	0.4818	0.6750	0.7636	0.5545	0.6364	0.6800	0.5200	0.5364	0.4909	0.5900	0.5761
11	STRCA	0.4400	0.6500	0.7333	0.5400	0.4900	0.5400	0.5444	0.4400	0.5600	0.4778	0.4800	0.6100	0.5222	0.5444	0.5100	0.5388
	CNN	0.5700	0.4800	0.8222	0.5700	0.6000	0.5300	0.7111	0.5900	0.5700	0.5556	0.5600	0.6000	0.5667	0.5778	0.5300	**0.5889**
	FBTRCA	0.4900	0.5800	0.8000	0.5900	0.4800	0.5200	0.7000	0.5200	0.5200	0.5444	0.5400	0.6000	0.5333	0.5667	0.5000	0.5656
12	STRCA	0.5455	0.5600	0.6900	0.7091	0.6091	0.5333	0.6889	0.6400	0.6100	0.5625	0.5111	0.6111	0.5111	0.4778	0.4600	0.5813
	CNN	0.5727	0.6500	0.8000	0.7182	0.6818	0.5222	0.6889	0.6000	0.7000	0.5875	0.4333	0.6333	0.4778	0.5667	0.4500	0.6055
	FBTRCA	0.4909	0.5900	0.7900	0.7091	0.7273	0.5444	0.7444	0.6900	0.6800	0.6500	0.5111	0.6333	0.6444	0.5333	0.4800	**0.6279**
13	STRCA	0.5083	0.6000	0.6909	0.5545	0.5000	0.4818	0.6909	0.6273	0.5818	0.4600	0.5200	0.4700	0.5300	0.6600	0.5100	0.5590
	CNN	0.4250	0.5455	0.7636	0.6909	0.5273	0.4818	0.7545	0.7091	0.5000	0.4900	0.5300	0.4800	0.5900	0.5500	0.5200	0.5705
	FBTRCA	0.3917	0.5727	0.7636	0.6818	0.5364	0.6091	0.7182	0.6636	0.5364	0.5300	0.5700	0.4900	0.5400	0.6100	0.4900	**0.5802**
14	STRCA	0.4833	0.5900	0.7700	0.6455	0.5455	0.5300	0.8200	0.6636	0.6091	0.6125	0.6000	0.5222	0.6444	0.6000	0.4400	0.6051
	CNN	0.5583	0.6200	0.8600	0.7000	0.6273	0.5200	0.7800	0.6636	0.6182	0.6500	0.6000	0.4889	0.6444	0.6667	0.5200	**0.6345**
	FBTRCA	0.5417	0.6200	0.8500	0.7818	0.6273	0.5000	0.7700	0.6364	0.5636	0.7000	0.6556	0.5333	0.5889	0.6556	0.4100	0.6289
15	STRCA	0.4455	0.5556	0.7400	0.6200	0.6900	0.6900	0.7364	0.6364	0.7364	0.5778	0.5667	0.5000	0.6200	0.4900	0.5600	0.6110
	CNN	0.4909	0.5667	0.6800	0.6200	0.6800	0.7000	0.7182	0.6273	0.7636	0.6111	0.5667	0.5222	0.5700	0.5600	0.5700	0.6164
	FBTRCA	0.4455	0.5889	0.7000	0.6500	0.7100	0.7200	0.7727	0.6909	0.7273	0.5889	0.6000	0.5333	0.5800	0.4700	0.6200	**0.6265**
Average	STRCA	0.5031	0.5833	0.7400	0.6505	0.5899	0.5407	0.7152	0.6251	0.6141	0.6054	0.5648	0.5626	0.5712	0.5642	0.5249	0.5970
	CNN	**0.5074**	0.5784	0.7668	0.6593	0.6339	0.5600	0.7390	0.6638	0.6380	0.6002	0.5617	0.5685	0.5789	**0.5728**	**0.5401**	0.6112
	FBTRCA	0.5059	**0.5884**	**0.7872**	**0.6827**	**0.6340**	**0.5730**	**0.7639**	**0.6649**	**0.6411**	**0.6233**	**0.5927**	**0.5757**	**0.5845**	0.5718	0.5345	**0.6216**

Table 5. Deviation of Classification Accuracies of Dataset I (RP) Across Ten Folds (Movement vs Movement)

Subject	Method	Motion Pair															Average
		EF-EE	EF-SU	EF-PR	EF-HC	EF-HO	EE-SU	EE-PR	EE-HC	EE-HO	SU-PR	SU-HC	SU-HO	PR-HC	PR-HO	HC-HO	
1	STRCA	0.1610	0.1700	0.0614	0.1134	0.1973	0.0966	0.1088	0.1548	0.1385	0.1673	0.1330	0.1366	0.1578	0.1174	0.1874	0.1401
	CNN	0.1687	0.1174	0.0643	0.2102	0.0939	0.1434	0.0717	0.1717	0.1629	0.1386	0.1304	0.1171	0.2011	0.1418	0.1549	**0.1392**
	FBTRCA	0.1427	0.1229	0.0862	0.1472	0.1592	0.1054	0.1032	0.1728	0.1548	0.1677	0.1386	0.0944	0.2261	0.1252	0.2044	0.1434
2	STRCA	0.2111	0.1160	0.2014	0.1650	0.1767	0.1075	0.1958	0.1969	0.2098	0.1476	0.2111	0.1350	0.0949	0.1418	0.1633	0.1649
	CNN	0.1418	0.2068	0.1197	0.1874	0.1700	0.1581	0.0667	0.1955	0.1969	0.1506	0.2132	0.0789	0.1729	0.1663	0.1687	0.1596
	FBTRCA	0.1636	0.1549	0.1075	0.2132	0.1874	0.1780	0.1160	0.1687	0.1549	0.0632	0.2635	0.1197	0.1792	0.1252	0.1563	**0.1568**
3	STRCA	0.1511	0.0675	0.1054	0.0614	0.1287	0.0876	0.1337	0.0939	0.1398	0.2267	0.0973	0.1811	0.1640	0.1419	0.1330	0.1275
	CNN	0.1441	0.1174	0.1449	0.1032	0.1033	0.1269	0.1247	0.0862	0.1317	0.1972	0.1907	0.1587	0.1405	0.1376	0.1693	0.1384
	FBTRCA	0.1375	0.1354	0.1059	0.0636	0.0516	0.1524	0.0994	0.0904	0.1174	0.1208	0.2369	0.1581	0.1261	0.1179	0.1054	**0.1213**
4	STRCA	0.2153	0.1150	0.0939	0.1182	0.1289	0.1303	0.1118	0.1245	0.1289	0.1713	0.1150	0.1354	0.1606	0.1287	0.0857	0.1309
	CNN	0.1024	0.1067	0.1154	0.1195	0.1212	0.1289	0.0883	0.1364	0.0904	0.1317	0.1828	0.1101	0.1359	0.1197	0.1050	**0.1196**
	FBTRCA	0.1427	0.0614	0.0796	0.1245	0.1359	0.1342	0.0977	0.1405	0.1150	0.1506	0.1385	0.1494	0.1828	0.1317	0.1197	0.1269
5	STRCA	0.1450	0.1118	0.1216	0.0748	0.1488	0.1333	0.1080	0.1476	0.1563	0.1713	0.1269	0.1333	0.1059	0.1337	0.1581	**0.1318**
	CNN	0.1512	0.1289	0.1197	0.1197	0.1227	0.1350	0.1663	0.1252	0.2058	0.1430	0.2058	0.1160	0.1247	0.1155	0.1703	0.1433
	FBTRCA	0.1150	0.1216	0.1615	0.1485	0.1437	0.1179	0.1317	0.1265	0.1932	0.1337	0.1333	0.0949	0.1197	0.1229	0.1874	0.1368
6	STRCA	0.1470	0.1592	0.0777	0.1606	0.1485	0.1372	0.1054	0.1369	0.0717	0.1748	0.1252	0.1619	0.1565	0.1419	0.1764	**0.1387**
	CNN	0.1097	0.1649	0.1021	0.1300	0.1434	0.1684	0.0820	0.1533	0.1197	0.1581	0.1687	0.1075	0.1959	0.1768	0.1398	0.1414
	FBTRCA	0.1544	0.1548	0.0750	0.1359	0.1385	0.0796	0.1366	0.1757	0.1286	0.1350	0.1430	0.1619	0.1467	0.1972	0.1197	0.1388
7	STRCA	0.0946	0.0878	0.1197	0.1118	0.1437	0.1964	0.1512	0.1286	0.1216	0.1853	0.1838	0.1567	0.1252	0.1647	0.1197	0.1394
	CNN	0.1192	0.1067	0.1592	0.1674	0.0835	0.1738	0.1342	0.1500	0.0939	0.1247	0.0789	0.2025	0.0966	0.1059	0.1989	0.1330
	FBTRCA	0.0896	0.0796	0.1500	0.1227	0.1032	0.1372	0.1227	0.1629	0.1138	0.1252	0.1792	0.1075	0.0949	0.1337	0.1494	**0.1248**
8	STRCA	0.1641	0.2204	0.1671	0.1286	0.1342	0.0862	0.1985	0.1385	0.1533	0.2011	0.1101	0.1814	0.1567	0.1398	0.1524	0.1555
	CNN	0.1732	0.1545	0.1878	0.1197	0.1054	0.1533	0.1966	0.1425	0.1434	0.1969	0.1265	0.1829	0.1716	0.1265	0.1430	0.1549
	FBTRCA	0.1669	0.1138	0.1777	0.1372	0.0748	0.1606	0.1780	0.1355	0.1372	0.1619	0.1317	0.2098	0.1265	0.1135	0.1080	**0.1422**
9	STRCA	0.1364	0.1907	0.0835	0.1138	0.1606	0.0878	0.1592	0.1271	0.1355	0.1886	0.1687	0.1434	0.1449	0.1751	0.1619	**0.1451**
	CNN	0.0962	0.1359	0.1545	0.1450	0.1246	0.1717	0.1150	0.1985	0.2227	0.1647	0.2234	0.1663	0.1449	0.1687	0.0789	0.1541
	FBTRCA	0.1349	0.1684	0.1663	0.1425	0.1289	0.1289	0.0939	0.1728	0.1472	0.1054	0.2413	0.1337	0.2183	0.1054	0.1247	0.1475
10	STRCA	0.0686	0.1359	0.1361	0.1557	0.1289	0.1497	0.1270	0.1289	0.1054	0.1985	0.1792	0.1567	0.1603	0.1300	0.1265	0.1392
	CNN	0.1386	0.1197	0.1270	0.1286	0.1050	0.1592	0.1721	0.1071	0.1917	0.1780	0.1578	0.1524	0.1858	0.1649	0.1265	0.1476
	FBTRCA	0.1128	0.1359	0.1245	0.1170	0.0904	0.1054	0.1493	0.1150	0.1684	0.1818	0.1619	0.1932	0.1512	0.1369	0.0994	**0.1362**
11	STRCA	0.1578	0.0707	0.1405	0.1265	0.1524	0.1174	0.1330	0.1506	0.2271	0.1576	0.1549	0.2183	0.1576	0.1848	0.1197	**0.1513**
	CNN	0.1059	0.1619	0.1589	0.1889	0.1563	0.1337	0.1673	0.1663	0.1418	0.2160	0.2066	0.1563	0.1105	0.1721	0.1418	0.1590
	FBTRCA	0.1524	0.1751	0.1721	0.1524	0.1549	0.1549	0.1177	0.1687	0.1687	0.1223	0.1506	0.1333	0.1021	0.1848	0.1764	0.1524
12	STRCA	0.2010	0.1430	0.1853	0.0939	0.1359	0.1463	0.2271	0.2366	0.1370	0.1693	0.1073	0.0944	0.2042	0.1288	0.1430	0.1569
	CNN	0.1821	0.1650	0.1247	0.1385	0.1500	0.1054	0.1874	0.1247	0.0667	0.1324	0.1430	0.1576	0.0915	0.1772	0.0707	**0.1345**
	FBTRCA	0.2151	0.2378	0.1449	0.1533	0.1714	0.0973	0.1660	0.1449	0.1687	0.1936	0.1405	0.1391	0.0876	0.1721	0.1549	0.1592
13	STRCA	0.1776	0.1926	0.1150	0.1385	0.1071	0.1821	0.0878	0.1684	0.1067	0.1713	0.1619	0.1337	0.1160	0.1647	0.1101	**0.1422**
	CNN	0.1329	0.1714	0.2019	0.1227	0.1197	0.2187	0.1054	0.1118	0.1831	0.1969	0.1567	0.1398	0.1729	0.1650	0.1619	0.1574
	FBTRCA	0.1419	0.1870	0.1497	0.1618	0.1572	0.1488	0.1088	0.1425	0.1000	0.2214	0.1059	0.1449	0.2119	0.1370	0.1101	0.1486
14	STRCA	0.0657	0.1197	0.0483	0.1246	0.1660	0.1494	0.1033	0.1054	0.2012	0.1713	0.1829	0.1486	0.2082	0.1673	0.1713	0.1422
	CNN	0.0883	0.1687	0.1075	0.0963	0.1385	0.1398	0.1033	0.1870	0.1408	0.2189	0.1194	0.1903	0.1463	0.1048	0.1989	0.1433
	FBTRCA	0.0708	0.1229	0.0850	0.1067	0.1450	0.1155	0.1160	0.1212	0.2134	0.1687	0.0973	0.1148	0.1963	0.0973	0.1524	**0.1282**
15	STRCA	0.1000	0.1656	0.1075	0.1229	0.1197	0.1524	0.1512	0.1660	0.0796	0.1640	0.1105	0.1080	0.1476	0.1449	0.1174	**0.1305**
	CNN	0.1150	0.1430	0.1398	0.1476	0.1135	0.0816	0.1088	0.1738	0.1227	0.1309	0.1523	0.1054	0.1252	0.1838	0.1337	0.1318
	FBTRCA	0.1246	0.1660	0.1333	0.1434	0.1853	0.1476	0.1071	0.1434	0.1355	0.2163	0.1829	0.1021	0.1476	0.1636	0.1549	0.1502
Average	STRCA	0.1464	**0.1377**	**0.1176**	**0.1206**	0.1452	**0.1307**	0.1401	0.1470	**0.1408**	0.1777	**0.1445**	0.1483	0.1507	0.1470	0.1417	0.1424
	CNN	**0.1313**	0.1446	0.1352	0.1416	**0.1234**	0.1465	0.1260	0.1487	0.1476	0.1652	0.1637	0.1428	**0.1477**	0.1484	0.1442	0.1438
	FBTRCA	0.1377	0.1425	0.1280	0.1380	0.1352	0.1309	**0.1229**	**0.1454**	0.1478	**0.1512**	0.1630	**0.1371**	0.1545	**0.1376**	**0.1415**	**0.1409**

Table 6. Mean of Classification Accuracies of Dataset I (RP) Across Ten Folds (Movement vs Resting)

Subject	Method	Motion Pair						Average
		EF-RE	EE-RE	SU-RE	PR-RE	HC-RE	HO-RE	
1	STRCA	0.8909	0.8727	0.8778	0.8300	0.8800	0.8600	0.8686
	CNN	0.9364	0.8818	0.9000	0.8800	0.8700	0.9000	0.8947
	FBTRCA	0.9364	0.8909	0.9444	0.9100	0.9200	0.9100	**0.9186**
2	STRCA	0.8600	0.8600	0.8100	0.7900	0.8100	0.8100	0.8233
	CNN	0.8200	0.8900	0.8600	0.8400	0.7900	0.8100	0.8350
	FBTRCA	0.9100	0.9100	0.8800	0.8300	0.8500	0.8800	**0.8767**
3	STRCA	0.8833	0.9000	0.8600	0.8700	0.8091	0.8600	0.8637
	CNN	0.8833	0.9583	0.8900	0.9000	0.8545	0.8600	0.8910
	FBTRCA	0.9250	0.9667	0.9000	0.8800	0.8545	0.9200	**0.9077**
4	STRCA	0.9000	0.9364	0.9000	0.9100	0.9000	0.8700	0.9027
	CNN	0.9182	0.9455	0.9100	0.8500	0.9091	0.8400	0.8955
	FBTRCA	0.9273	0.9545	0.9200	0.9000	0.9091	0.8700	**0.9135**
5	STRCA	0.7091	0.8000	0.7500	0.7900	0.7500	0.7600	0.7598
	CNN	0.8273	0.8800	0.8100	0.7900	0.8000	0.7800	0.8145
	FBTRCA	0.8091	0.8900	0.8100	0.7900	0.8200	0.7700	**0.8148**
6	STRCA	0.9667	0.9417	0.9182	0.9222	0.9182	0.8727	0.9233
	CNN	0.9583	0.9583	0.9000	0.9000	0.9364	0.8727	0.9210
	FBTRCA	0.9667	0.9500	0.9091	0.9222	0.9182	0.9000	**0.9277**
7	STRCA	0.8083	0.7500	0.7455	0.6909	0.6636	0.6727	0.7218
	CNN	0.7583	0.7833	0.7182	0.7000	0.6182	0.6545	0.7054
	FBTRCA	0.8000	0.7333	0.7455	0.7182	0.6364	0.7545	**0.7313**
8	STRCA	0.8667	0.8833	0.8273	0.8182	0.8545	0.8727	0.8538
	CNN	0.9417	0.8667	0.8091	0.8545	0.9000	0.8818	0.8756
	FBTRCA	0.9583	0.9000	0.8727	0.8636	0.8909	0.8909	**0.8961**
9	STRCA	0.8417	0.7917	0.7364	0.7636	0.6727	0.7455	0.7586
	CNN	0.8667	0.8583	0.7273	0.8182	0.8636	0.8455	0.8299
	FBTRCA	0.8917	0.8417	0.7727	0.8455	0.8273	0.8091	**0.8313**
10	STRCA	0.9636	0.9182	0.8600	0.7455	0.8400	0.8800	0.8679
	CNN	0.9091	0.8909	0.8600	0.8455	0.8800	0.8400	0.8709
	FBTRCA	0.9455	0.9273	0.8300	0.8545	0.8300	0.8400	**0.8712**
11	STRCA	0.7900	0.7600	0.7200	0.6333	0.8100	0.7100	0.7372
	CNN	0.8300	0.7800	0.7400	0.7444	0.8400	0.7700	0.7841
	FBTRCA	0.8700	0.8100	0.7800	0.8000	0.8300	0.8100	**0.8167**
12	STRCA	0.8455	0.7900	0.8111	0.7222	0.7500	0.7400	0.7765
	CNN	0.8273	0.7900	0.8333	0.8000	0.8100	0.7900	0.8084
	FBTRCA	0.9000	0.8200	0.8556	0.7778	0.8400	0.8700	**0.8439**
13	STRCA	0.9000	0.8917	0.7818	0.7636	0.7909	0.8000	0.8213
	CNN	0.9000	0.8917	0.8364	0.8455	0.8364	0.8273	0.8562
	FBTRCA	0.9500	0.9083	0.8273	0.8909	0.8273	0.8455	**0.8749**
14	STRCA	0.8667	0.9083	0.8600	0.7500	0.8909	0.8182	0.8490
	CNN	0.9083	0.9500	0.8500	0.7600	0.9091	0.8727	**0.8750**
	FBTRCA	0.8750	0.9333	0.8200	0.8000	0.9182	0.8636	0.8684
15	STRCA	0.9182	0.9167	0.8800	0.9091	0.9182	0.8727	0.9025
	CNN	0.8909	0.9250	0.8900	0.9273	0.8909	0.8455	0.8949
	FBTRCA	0.9455	0.9333	0.9000	0.8909	0.8909	0.8727	**0.9056**
Average	STRCA	0.8674	0.8614	0.8225	0.7939	0.8172	0.8096	0.8287
	CNN	0.8784	0.8833	0.8356	0.8304	0.8472	0.8260	0.8501
	FBTRCA	**0.9074**	**0.8913**	**0.8512**	**0.8449**	**0.8508**	**0.8538**	**0.8666**

Table 7. Deviation of Classification Accuracies of Dataset I (RP) Across Ten Folds (Movement vs Resting)

Subject	Method	Motion Pair						Average
		EF-RE	EE-RE	SU-RE	PR-RE	HC-RE	HO-RE	
1	STRCA	0.1032	0.0977	0.1430	0.1567	0.1229	0.1350	0.1264
	CNN	0.0963	0.0963	0.0820	0.1033	0.0949	0.0943	0.0945
	FBTRCA	0.0748	0.0575	0.0586	0.1101	0.0919	0.0876	**0.0801**
2	STRCA	0.1265	0.0843	0.1197	0.0994	0.1197	0.0994	0.1082
	CNN	0.1398	0.0738	0.0699	0.1174	0.1370	0.0994	0.1062
	FBTRCA	0.1101	0.0738	0.0632	0.1059	0.0972	0.1398	**0.0983**
3	STRCA	0.1192	0.0351	0.0699	0.1059	0.0904	0.1430	**0.0939**
	CNN	0.0805	0.0439	0.1197	0.1155	0.1300	0.0843	0.0957
	FBTRCA	0.0829	0.0583	0.0816	0.1549	0.0977	0.1033	0.0965
4	STRCA	0.0796	0.0963	0.0816	0.0876	0.0671	0.1160	**0.0880**
	CNN	0.0796	0.0636	0.0738	0.1179	0.0857	0.2011	0.1036
	FBTRCA	0.0835	0.0883	0.0919	0.1054	0.1134	0.2111	0.1156
5	STRCA	0.1703	0.1563	0.1509	0.1287	0.1650	0.1647	0.1560
	CNN	0.0796	0.0789	0.1101	0.1370	0.1155	0.1135	**0.1058**
	FBTRCA	0.1246	0.1287	0.1449	0.1287	0.0919	0.1160	0.1224
6	STRCA	0.0583	0.0562	0.0904	0.0915	0.1088	0.1067	0.0853
	CNN	0.0439	0.0439	0.1000	0.0820	0.0748	0.0977	**0.0737**
	FBTRCA	0.0583	0.0430	0.0742	0.1177	0.1170	0.1000	0.0850
7	STRCA	0.1115	0.0786	0.0575	0.0878	0.1138	0.1150	**0.0940**
	CNN	0.1270	0.1054	0.1088	0.0614	0.1342	0.1472	0.1140
	FBTRCA	0.0896	0.0861	0.0939	0.1088	0.1286	0.1289	0.1060
8	STRCA	0.0703	0.0896	0.0796	0.1485	0.0767	0.0977	**0.0937**
	CNN	0.1043	0.1125	0.1000	0.1150	0.0904	0.0862	0.1014
	FBTRCA	0.0810	0.0766	0.1150	0.0883	0.1118	0.1032	0.0960
9	STRCA	0.1142	0.0708	0.1938	0.2019	0.1227	0.1118	0.1359
	CNN	0.0583	0.1669	0.1868	0.0857	0.0982	0.1138	0.1183
	FBTRCA	0.0883	0.1329	0.1154	0.1359	0.1385	0.0904	**0.1169**
10	STRCA	0.0636	0.0671	0.0699	0.1197	0.1430	0.1033	0.0944
	CNN	0.0857	0.0835	0.0966	0.1425	0.1135	0.1430	0.1108
	FBTRCA	0.0636	0.0717	0.0949	0.1227	0.0675	0.1174	**0.0896**
11	STRCA	0.1197	0.1174	0.1398	0.1391	0.1370	0.1370	0.1317
	CNN	0.0675	0.1549	0.1350	0.1660	0.0966	0.1252	0.1242
	FBTRCA	0.0949	0.1197	0.1033	0.1640	0.1252	0.1370	**0.1240**
12	STRCA	0.0963	0.1197	0.1288	0.1309	0.1179	0.2119	0.1343
	CNN	0.1000	0.1524	0.1410	0.0876	0.1524	0.2025	0.1393
	FBTRCA	0.0671	0.1229	0.1576	0.1171	0.1075	0.1494	**0.1203**
13	STRCA	0.0861	0.0791	0.1300	0.1300	0.1663	0.0575	0.1081
	CNN	0.1024	0.0966	0.1342	0.1289	0.1118	0.0904	0.1107
	FBTRCA	0.0805	0.0998	0.1790	0.0835	0.0904	0.0963	**0.1049**
14	STRCA	0.0896	0.0829	0.1174	0.1080	0.1197	0.1212	0.1065
	CNN	0.0615	0.0583	0.1269	0.1075	0.1050	0.0636	**0.0871**
	FBTRCA	0.0900	0.0861	0.1398	0.0943	0.1000	0.1071	0.1029
15	STRCA	0.0796	0.0878	0.1317	0.0857	0.0671	0.1150	0.0945
	CNN	0.0939	0.0615	0.0994	0.0717	0.1032	0.0963	**0.0877**
	FBTRCA	0.0767	0.0861	0.1054	0.1032	0.1032	0.1150	0.0983
Average	STRCA	0.0992	**0.0879**	0.1136	0.1214	0.1159	0.1223	0.1101
	CNN	0.0880	0.0928	0.1123	**0.1093**	0.1095	**0.1172**	0.1049
	FBTRCA	**0.0844**	0.0888	**0.1079**	0.1160	**0.1054**	0.1202	**0.1038**

Table 8. Mean of Classification Accuracies of Dataset I (RP+MMP) Across Ten Folds (Movement vs Movement)

Subject	Method	Motion Pair															Average
		EF-EE	EF-SU	EF-PR	EF-HC	EF-HO	EE-SU	EE-PR	EE-HC	EE-HO	SU-PR	SU-HC	SU-HO	PR-HC	PR-HO	HC-HO	
1	STRCA	0.4917	0.6700	0.8273	0.7182	0.5909	0.5800	0.7273	0.7273	0.6000	0.8111	0.7111	0.6333	0.6000	0.6200	0.6600	0.6645
	CNN	0.5417	0.6900	0.9091	0.7636	0.7364	0.6400	0.9000	0.7909	0.7364	0.9111	0.7778	0.7556	0.5800	0.6500	0.6300	0.7342
	FBTRCA	0.5500	0.7100	0.9273	0.8091	0.7273	0.6900	0.9182	0.8364	0.7545	0.9222	0.8000	0.7889	0.5900	0.6900	0.6500	**0.7576**
2	STRCA	0.5300	0.5700	0.8700	0.6000	0.5200	0.5600	0.8100	0.6100	0.4900	0.7400	0.4900	0.5500	0.6400	0.6700	0.5000	0.6100
	CNN	0.5100	0.6300	0.9100	0.5700	0.5000	0.6300	0.8600	0.5300	0.6300	0.7600	0.5200	0.6100	0.7000	0.7200	0.4500	0.6353
	FBTRCA	0.5900	0.6500	0.9400	0.5700	0.5600	0.6100	0.8900	0.6100	0.6600	0.7700	0.5900	0.5900	0.7100	0.7400	0.4200	**0.6600**
3	STRCA	0.5083	0.7000	0.7500	0.8364	0.7600	0.5800	0.7400	0.9273	0.8400	0.5500	0.6444	0.7000	0.5333	0.6500	0.7111	0.6954
	CNN	0.6917	0.8100	0.7900	0.9455	0.9200	0.7400	0.8400	0.9455	0.9600	0.7125	0.7333	0.8000	0.6000	0.5500	0.6333	0.7781
	FBTRCA	0.7333	0.8500	0.8500	0.9273	0.9100	0.7700	0.8500	0.9545	0.9600	0.6875	0.8000	0.7875	0.5889	0.7000	0.6333	**0.8002**
4	STRCA	0.5583	0.6182	0.9545	0.8833	0.8000	0.5818	0.9273	0.8500	0.7818	0.9000	0.8455	0.8500	0.5909	0.5700	0.6000	0.7541
	CNN	0.5833	0.7091	0.9909	0.9417	0.8455	0.7000	0.9636	0.9167	0.8545	0.9800	0.9091	0.9400	0.6000	0.6300	0.6273	0.8128
	FBTRCA	0.6417	0.7000	0.9727	0.9500	0.8636	0.6909	0.9636	0.9250	0.8818	0.9800	0.9545	0.9500	0.6000	0.6700	0.6455	**0.8260**
5	STRCA	0.5818	0.5909	0.8182	0.6818	0.6545	0.7100	0.9100	0.8500	0.8000	0.5900	0.6000	0.6000	0.5700	0.5100	0.5800	0.6698
	CNN	0.6182	0.7364	0.8455	0.8091	0.7727	0.7700	0.9600	0.8800	0.7900	0.6000	0.5700	0.4900	0.6200	0.5200	0.5300	**0.7008**
	FBTRCA	0.5818	0.6273	0.9091	0.8000	0.7273	0.7300	0.9700	0.8400	0.8300	0.6400	0.5300	0.5000	0.5700	0.5600	0.5600	0.6917
6	STRCA	0.5000	0.6000	0.9333	0.7364	0.8364	0.5455	0.9333	0.6545	0.8091	0.6625	0.5900	0.7100	0.6750	0.6250	0.6400	0.6967
	CNN	0.6250	0.6273	0.9333	0.8182	0.8727	0.6091	0.9111	0.6636	0.8545	0.6625	0.5500	0.6900	0.6125	0.5625	0.6200	0.7075
	FBTRCA	0.6083	0.7091	0.9667	0.7727	0.8818	0.6091	0.9222	0.6000	0.8545	0.7000	0.4800	0.6700	0.6875	0.6000	0.6200	**0.7121**
7	STRCA	0.4917	0.6182	0.8455	0.7091	0.6909	0.5545	0.8636	0.7182	0.7091	0.6300	0.5500	0.5500	0.5900	0.5200	0.4900	0.6354
	CNN	0.5583	0.6455	0.9364	0.7455	0.8455	0.5273	0.8909	0.7364	0.7091	0.6200	0.6000	0.6100	0.6200	0.5000	0.5900	**0.6756**
	FBTRCA	0.5417	0.6636	0.9364	0.7636	0.6909	0.5818	0.8909	0.7364	0.7000	0.6800	0.5800	0.5700	0.6600	0.5200	0.4900	0.6670
8	STRCA	0.4583	0.6182	0.8545	0.7727	0.7000	0.5636	0.8818	0.6727	0.6455	0.7700	0.6400	0.7000	0.5000	0.5500	0.5300	0.6572
	CNN	0.4917	0.6545	0.9455	0.7455	0.7818	0.6000	0.9364	0.6727	0.7455	0.8500	0.5800	0.6300	0.5500	0.5200	0.5500	0.6836
	FBTRCA	0.4917	0.7364	0.9364	0.8000	0.7727	0.6364	0.9273	0.7273	0.7636	0.8600	0.7000	0.6800	0.5400	0.6100	0.5300	**0.7141**
9	STRCA	0.7083	0.7273	0.8364	0.7636	0.7545	0.6455	0.7818	0.7364	0.7273	0.6400	0.4900	0.5600	0.5700	0.6200	0.5900	0.6767
	CNN	0.8417	0.8182	0.9455	0.7818	0.8091	0.6909	0.8909	0.8091	0.8091	0.5900	0.4800	0.7300	0.5400	0.7100	0.5700	0.7344
	FBTRCA	0.8917	0.7545	0.9455	0.8364	0.8091	0.7455	0.9000	0.7727	0.8273	0.6200	0.4500	0.7000	0.5800	0.7000	0.6600	**0.7462**
10	STRCA	0.5167	0.5364	0.7250	0.8545	0.6455	0.5545	0.6583	0.7818	0.7636	0.6545	0.6800	0.7200	0.6545	0.4636	0.5600	0.6513
	CNN	0.5083	0.6000	0.7250	0.8091	0.7636	0.5909	0.7917	0.8364	0.7636	0.6182	0.8200	0.7200	0.6000	0.5818	0.5200	0.6832
	FBTRCA	0.4833	0.6000	0.7750	0.8545	0.7364	0.6000	0.7583	0.8455	0.7636	0.6636	0.8000	0.7000	0.6455	0.5455	0.6100	**0.6921**
11	STRCA	0.4900	0.6600	0.6889	0.6100	0.5800	0.6700	0.7000	0.5700	0.5700	0.6444	0.6700	0.6200	0.5111	0.5778	0.4900	0.6035
	CNN	0.5100	0.6900	0.7667	0.6100	0.6600	0.5900	0.7111	0.6500	0.5800	0.6333	0.5800	0.7200	0.5000	0.6000	0.4400	0.6161
	FBTRCA	0.5300	0.7100	0.8000	0.7000	0.6700	0.6200	0.8000	0.6700	0.6400	0.6444	0.6700	0.7500	0.5222	0.5556	0.3800	**0.6441**
12	STRCA	0.5636	0.6100	0.7900	0.7182	0.7364	0.6333	0.7778	0.6700	0.7100	0.6250	0.5667	0.5889	0.5667	0.4444	0.5400	0.6361
	CNN	0.6545	0.5600	0.8900	0.7909	0.7818	0.7222	0.8889	0.6600	0.8100	0.6625	0.4667	0.7000	0.5333	0.4889	0.4900	0.6733
	FBTRCA	0.6636	0.6500	0.9200	0.7818	0.8000	0.6778	0.9111	0.7400	0.8400	0.8000	0.7000	0.7444	0.6222	0.5444	0.5100	**0.7270**
13	STRCA	0.5083	0.5909	0.7636	0.6909	0.5182	0.5545	0.8182	0.7455	0.6636	0.6100	0.6200	0.4600	0.5300	0.6400	0.5200	0.6156
	CNN	0.4500	0.5727	0.8455	0.7182	0.6636	0.6455	0.8182	0.8182	0.6273	0.5900	0.6200	0.5300	0.5700	0.5500	0.5800	0.6399
	FBTRCA	0.5250	0.6273	0.8818	0.8182	0.6636	0.6545	0.9091	0.8182	0.6818	0.6500	0.7000	0.5900	0.5200	0.5500	0.5700	**0.6773**
14	STRCA	0.5250	0.6100	0.8900	0.7545	0.6818	0.6400	0.8300	0.8000	0.6000	0.6750	0.5889	0.6444	0.5556	0.6556	0.4800	0.6621
	CNN	0.6000	0.6900	0.9400	0.8727	0.8000	0.6100	0.9500	0.7636	0.7455	0.7500	0.5889	0.6778	0.6667	0.6889	0.4900	0.7223
	FBTRCA	0.6250	0.7000	0.9300	0.8545	0.8727	0.6100	0.9300	0.8273	0.7727	0.8000	0.6556	0.6556	0.6000	0.7444	0.4700	**0.7365**
15	STRCA	0.3727	0.7000	0.7900	0.6800	0.8000	0.7300	0.8727	0.6909	0.8091	0.6778	0.6667	0.6333	0.6600	0.5800	0.6600	0.6882
	CNN	0.5182	0.6889	0.8700	0.7200	0.8500	0.8200	0.8818	0.6364	0.7636	0.6333	0.6333	0.6444	0.6200	0.4600	0.6400	0.6920
	FBTRCA	0.4455	0.7222	0.9500	0.7000	0.8600	0.7500	0.9091	0.7182	0.8545	0.7444	0.6667	0.6222	0.6600	0.5500	0.5800	**0.7155**
Average	STRCA	0.5203	0.6280	0.8225	0.7340	0.6846	0.6069	0.8155	0.7336	0.7013	0.6787	0.6235	0.6347	0.5831	0.5798	**0.5701**	0.6611
	CNN	0.5802	0.6748	0.8829	0.7761	**0.7735**	0.6591	0.8796	0.7540	0.7586	0.7049	0.6286	0.6832	0.5942	0.5821	0.5574	0.6993
	FBTRCA	**0.5935**	**0.6940**	**0.9094**	**0.7959**	0.7697	**0.6651**	**0.8967**	**0.7748**	**0.7856**	**0.7441**	**0.6718**	**0.6866**	**0.6064**	**0.6187**	0.5553	**0.7178**

Table 9. Deviation of Classification Accuracies of Dataset I (RP+MMP) Across Ten Folds (Movement vs Movement)

Subject	Method	Motion Pair															Average
		EF-EE	EF-SU	EF-PR	EF-HC	EF-HO	EE-SU	EE-PR	EE-HC	EE-HO	SU-PR	SU-HC	SU-HO	PR-HC	PR-HO	HC-HO	
1	STRCA	0.1819	0.0949	0.1629	0.1170	0.1560	0.2044	0.1355	0.1134	0.1671	0.2098	0.1500	0.1391	0.1247	0.1033	0.1713	0.1487
	CNN	0.1483	0.0876	0.0857	0.1150	0.1572	0.1430	0.0796	0.0862	0.0904	0.0703	0.0907	0.1366	0.1317	0.1269	0.1337	0.1122
	FBTRCA	0.0805	0.1287	0.0575	0.0904	0.1134	0.0994	0.1000	0.1271	0.0963	0.0915	0.1366	0.1105	0.1449	0.1197	0.1650	**0.1108**
2	STRCA	0.1947	0.1703	0.1337	0.1633	0.1135	0.1265	0.1663	0.1101	0.2424	0.1350	0.1853	0.1434	0.1713	0.1494	0.1414	0.1564
	CNN	0.1197	0.1252	0.0876	0.1947	0.1333	0.1160	0.1350	0.1160	0.1252	0.1265	0.1932	0.1969	0.1563	0.1229	0.2068	**0.1437**
	FBTRCA	0.0876	0.1780	0.0699	0.2111	0.1350	0.1197	0.1101	0.1101	0.2221	0.2003	0.2025	0.1729	0.1370	0.0966	0.1814	0.1489
3	STRCA	0.2058	0.1247	0.1269	0.0575	0.1350	0.1687	0.1713	0.0939	0.1075	0.1687	0.1721	0.1344	0.1021	0.1419	0.1753	0.1391
	CNN	0.1182	0.0994	0.0738	0.0636	0.0632	0.1174	0.1075	0.0469	0.0516	0.1868	0.1589	0.1467	0.1829	0.1882	0.1486	0.1169
	FBTRCA	0.1230	0.1434	0.1080	0.0575	0.0876	0.1252	0.1080	0.0479	0.0966	0.1792	0.1366	0.1324	0.0915	0.1467	0.1177	**0.1134**
4	STRCA	0.1524	0.1032	0.0643	0.1125	0.1342	0.1828	0.0575	0.1097	0.1434	0.0816	0.1289	0.1354	0.1372	0.1889	0.1067	0.1226
	CNN	0.0962	0.0575	0.0287	0.0562	0.0862	0.1138	0.0469	0.1039	0.1067	0.0422	0.0742	0.0516	0.1369	0.1160	0.1000	**0.0811**
	FBTRCA	0.1364	0.1216	0.0439	0.0703	0.0643	0.1497	0.0636	0.0917	0.1054	0.0422	0.0773	0.0707	0.1300	0.1160	0.1170	0.0933
5	STRCA	0.1227	0.1728	0.1286	0.1154	0.1472	0.1524	0.1101	0.1179	0.1414	0.1595	0.2404	0.1944	0.1418	0.1524	0.1033	0.1467
	CNN	0.1954	0.1512	0.1054	0.0796	0.1500	0.1252	0.0516	0.0919	0.0738	0.1563	0.1494	0.1101	0.1317	0.1033	0.1494	0.1216
	FBTRCA	0.1828	0.0796	0.0742	0.1032	0.1286	0.0949	0.0675	0.1075	0.0949	0.1265	0.1252	0.1944	0.1567	0.1075	0.1647	**0.1205**
6	STRCA	0.1800	0.1300	0.0574	0.1938	0.1342	0.1355	0.0777	0.1592	0.1246	0.1773	0.1729	0.1370	0.1054	0.1768	0.1955	0.1438
	CNN	0.0982	0.1890	0.0777	0.1134	0.0977	0.0862	0.1148	0.1138	0.0977	0.1672	0.1269	0.0994	0.1376	0.1693	0.1989	**0.1259**
	FBTRCA	0.1182	0.1808	0.0537	0.1437	0.1216	0.1054	0.0750	0.1973	0.0878	0.1344	0.1814	0.1337	0.1215	0.2555	0.1229	0.1355
7	STRCA	0.1687	0.1592	0.1138	0.1592	0.1150	0.1938	0.0982	0.1088	0.1271	0.2058	0.1841	0.1509	0.1370	0.1874	0.1287	0.1492
	CNN	0.1043	0.1170	0.0748	0.1271	0.0862	0.1408	0.0835	0.1738	0.0717	0.1687	0.1414	0.1197	0.1687	0.1155	0.1663	**0.1240**
	FBTRCA	0.1195	0.1138	0.0748	0.1300	0.1369	0.0878	0.0835	0.1170	0.1425	0.1476	0.1398	0.1767	0.2221	0.1476	0.1197	0.1306
8	STRCA	0.1375	0.1032	0.0977	0.1372	0.1289	0.1118	0.0748	0.0977	0.1246	0.1160	0.2119	0.1247	0.1247	0.1581	0.1337	**0.1255**
	CNN	0.1544	0.1472	0.0767	0.1342	0.1067	0.1926	0.1216	0.1369	0.0835	0.1434	0.0919	0.1252	0.1650	0.2098	0.1269	0.1344
	FBTRCA	0.1072	0.1684	0.0748	0.1118	0.1071	0.1545	0.0939	0.1545	0.1369	0.0843	0.1155	0.1814	0.1174	0.1729	0.1418	0.1282
9	STRCA	0.1128	0.1603	0.1408	0.1227	0.1359	0.1385	0.0878	0.1512	0.1818	0.1430	0.1370	0.1265	0.1494	0.1932	0.1853	0.1444
	CNN	0.0917	0.0606	0.0636	0.1150	0.0904	0.1150	0.0835	0.1000	0.1088	0.2283	0.1549	0.1418	0.1265	0.1370	0.1829	0.1200
	FBTRCA	0.0883	0.1216	0.0469	0.1271	0.1317	0.1342	0.0904	0.0883	0.0516	0.1814	0.1354	0.1563	0.1619	0.1155	0.1578	**0.1192**
10	STRCA	0.1459	0.1000	0.1364	0.1300	0.1170	0.1841	0.1208	0.0767	0.1369	0.1907	0.1317	0.1814	0.1408	0.1088	0.1265	0.1352
	CNN	0.1270	0.1300	0.1472	0.1738	0.1497	0.1154	0.0982	0.1118	0.0977	0.2001	0.1229	0.1619	0.1434	0.1369	0.1814	0.1398
	FBTRCA	0.1561	0.1369	0.0883	0.1067	0.1000	0.1434	0.0998	0.0963	0.1227	0.1770	0.1414	0.0943	0.1246	0.1714	0.1595	**0.1279**
11	STRCA	0.2283	0.1506	0.1463	0.2079	0.1033	0.2452	0.1576	0.2058	0.1494	0.2082	0.1636	0.1476	0.1194	0.1148	0.1595	0.1672
	CNN	0.1969	0.0876	0.1223	0.1197	0.1578	0.1287	0.1304	0.1900	0.1476	0.1892	0.1751	0.1317	0.1757	0.1673	0.2171	0.1558
	FBTRCA	0.1636	0.1197	0.1148	0.1563	0.1494	0.1476	0.1366	0.2003	0.1578	0.1366	0.1829	0.2369	0.0915	0.1656	0.1033	**0.1509**
12	STRCA	0.1032	0.1969	0.1101	0.1684	0.0904	0.1288	0.1571	0.1494	0.1449	0.1318	0.2124	0.1486	0.1772	0.1889	0.2011	0.1540
	CNN	0.1271	0.1713	0.0994	0.1717	0.0878	0.1907	0.1283	0.1647	0.1663	0.1672	0.1366	0.0915	0.1640	0.1073	0.1370	0.1407
	FBTRCA	0.0963	0.2369	0.0632	0.1434	0.1032	0.2250	0.1148	0.1430	0.1350	0.0874	0.1288	0.0915	0.1304	0.1610	0.2234	**0.1389**
13	STRCA	0.1329	0.1928	0.1369	0.1227	0.1216	0.1317	0.0958	0.1118	0.1821	0.2234	0.1135	0.1838	0.1494	0.1506	0.1687	0.1478
	CNN	0.0805	0.1870	0.0862	0.1450	0.0963	0.1317	0.0857	0.1355	0.0904	0.1287	0.1476	0.2312	0.1337	0.1581	0.1751	**0.1342**
	FBTRCA	0.1574	0.1890	0.0862	0.0606	0.1216	0.1472	0.0857	0.1355	0.1071	0.2273	0.1155	0.1729	0.1317	0.1900	0.1418	0.1380
14	STRCA	0.1115	0.1197	0.0876	0.1606	0.1231	0.1578	0.0823	0.1032	0.1434	0.1787	0.1818	0.0703	0.2095	0.1223	0.1549	0.1338
	CNN	0.1165	0.1595	0.0699	0.0767	0.1032	0.1197	0.0527	0.1150	0.1197	0.1768	0.1576	0.0973	0.1656	0.1148	0.1449	**0.1193**
	FBTRCA	0.1318	0.1054	0.0675	0.1067	0.1150	0.1101	0.0675	0.0796	0.0982	0.1581	0.1610	0.1223	0.1829	0.1177	0.2111	0.1223
15	STRCA	0.1385	0.1818	0.1370	0.1229	0.1054	0.1252	0.1150	0.1067	0.1450	0.1610	0.0907	0.1391	0.1430	0.1398	0.1647	0.1344
	CNN	0.1488	0.2082	0.1160	0.0919	0.0972	0.1317	0.0748	0.1134	0.0977	0.1288	0.1177	0.1554	0.1874	0.2366	0.1506	0.1371
	FBTRCA	0.1938	0.2045	0.0707	0.1054	0.0966	0.1509	0.0742	0.1512	0.1150	0.1391	0.1481	0.1405	0.1075	0.1900	0.1033	**0.1327**
Average	STRCA	0.1545	0.1440	0.1187	0.1394	0.1240	0.1591	0.1139	0.1210	0.1508	0.1660	0.1651	0.1438	0.1422	0.1518	0.1544	0.1432
	CNN	**0.1282**	**0.1319**	0.0877	0.1185	**0.1109**	**0.1312**	0.0930	**0.1200**	**0.1019**	0.1520	**0.1359**	**0.1331**	0.1538	**0.1473**	0.1613	**0.1271**
	FBTRCA	0.1295	0.1485	**0.0730**	**0.1150**	0.1141	0.1330	**0.0914**	0.1232	0.1180	**0.1408**	0.1419	0.1458	**0.1368**	0.1516	**0.1487**	0.1274

Table 10. Mean of Classification Accuracies of Dataset I (RP+MMP) Across Ten Folds (Movement vs Resting)

Subject	Method	Motion Pair						Average
		EF-RE	EE-RE	SU-RE	PR-RE	HC-RE	HO-RE	
1	STRCA	0.8636	0.8545	0.8444	0.7300	0.7700	0.8000	0.8104
	CNN	0.9545	0.9000	0.9333	0.8700	0.8400	0.9200	0.9030
	FBTRCA	0.9727	0.9273	0.9444	0.8700	0.8500	0.9200	**0.9141**
2	STRCA	0.9300	0.9100	0.8600	0.7700	0.8400	0.8200	0.8550
	CNN	0.9500	0.9100	0.8800	0.8300	0.8000	0.7900	0.8600
	FBTRCA	0.9900	0.9400	0.9000	0.8500	0.8800	0.8700	**0.9050**
3	STRCA	0.9333	0.9417	0.8000	0.7600	0.7545	0.8200	0.8349
	CNN	0.9583	1.0000	0.9000	0.8900	0.8364	0.8700	0.9091
	FBTRCA	0.9583	1.0000	0.9000	0.8900	0.8091	0.9000	**0.9096**
4	STRCA	0.9545	0.9273	0.9400	0.7800	0.8000	0.8100	0.8686
	CNN	0.9727	0.9636	1.0000	0.8800	0.8818	0.8600	0.9264
	FBTRCA	0.9909	0.9636	1.0000	0.8700	0.8909	0.8800	**0.9326**
5	STRCA	0.8636	0.9400	0.7500	0.7000	0.7400	0.7400	0.7889
	CNN	0.9364	0.9600	0.8200	0.7800	0.8300	0.8100	0.8561
	FBTRCA	0.9364	0.9800	0.8100	0.7900	0.8100	0.8100	**0.8561**
6	STRCA	0.9833	0.9833	0.8273	0.9000	0.8455	0.8273	0.8944
	CNN	1.0000	1.0000	0.9455	0.9111	0.9364	0.8545	**0.9412**
	FBTRCA	0.9917	1.0000	0.9455	0.8889	0.9273	0.8818	0.9392
7	STRCA	0.8417	0.8750	0.7909	0.6545	0.6636	0.6364	0.7437
	CNN	0.9417	0.8583	0.7636	0.7091	0.6818	0.6636	0.7697
	FBTRCA	0.9417	0.8917	0.8455	0.7182	0.6818	0.7091	**0.7980**
8	STRCA	0.9750	0.9667	0.9364	0.8091	0.8545	0.9000	0.9069
	CNN	1.0000	0.9833	0.9000	0.8545	0.9273	0.9545	0.9366
	FBTRCA	0.9917	0.9833	0.9455	0.8545	0.9182	0.9455	**0.9398**
9	STRCA	0.9000	0.8833	0.6909	0.7455	0.6364	0.7182	0.7624
	CNN	0.9750	0.9750	0.8455	0.8000	0.8091	0.8636	0.8780
	FBTRCA	0.9833	0.9750	0.8455	0.8273	0.8455	0.8364	**0.8855**
10	STRCA	0.9000	0.9364	0.8100	0.7636	0.7100	0.8300	0.8250
	CNN	0.9273	0.9364	0.9000	0.8000	0.8100	0.8700	0.8739
	FBTRCA	0.9364	0.9636	0.9200	0.8636	0.8500	0.8900	**0.9039**
11	STRCA	0.8200	0.8400	0.8300	0.6889	0.7300	0.6500	0.7598
	CNN	0.8900	0.8800	0.8800	0.7778	0.8500	0.7800	0.8430
	FBTRCA	0.9300	0.9300	0.8600	0.7556	0.8600	0.8400	**0.8626**
12	STRCA	0.9273	0.9300	0.8444	0.6667	0.7900	0.6700	0.8047
	CNN	0.9091	0.9000	0.9111	0.8000	0.8500	0.8000	0.8617
	FBTRCA	0.9455	0.9200	0.8889	0.7556	0.8600	0.8400	**0.8683**
13	STRCA	0.9250	0.9250	0.7545	0.6909	0.7545	0.7909	0.8068
	CNN	0.9583	0.9750	0.8273	0.7727	0.7636	0.8455	0.8571
	FBTRCA	0.9750	0.9667	0.8455	0.8909	0.8182	0.8727	**0.8948**
14	STRCA	0.9500	0.9333	0.8300	0.7000	0.8364	0.7636	0.8356
	CNN	0.9833	0.9833	0.8700	0.8100	0.9364	0.9091	**0.9154**
	FBTRCA	0.9833	0.9750	0.9300	0.8400	0.9000	0.8455	0.9123
15	STRCA	0.9182	0.9167	0.8200	0.8091	0.7818	0.8182	0.8440
	CNN	0.9727	0.9667	0.9200	0.9000	0.8818	0.8273	0.9114
	FBTRCA	0.9818	0.9667	0.9400	0.8818	0.9364	0.8727	**0.9299**
Average	STRCA	0.9124	0.9175	0.8219	0.7446	0.7672	0.7730	0.8228
	CNN	0.9553	0.9461	0.8864	0.8257	0.8423	0.8412	0.8828
	FBTRCA	**0.9672**	**0.9589**	**0.9014**	**0.8364**	**0.8558**	**0.8609**	**0.8968**

Table 11. Deviation of Classification Accuracies of Dataset I (RP+MMP) Across Ten Folds (Movement vs Resting)

Subject	Method	Motion Pair						Average
		EF-RE	EE-RE	SU-RE	PR-RE	HC-RE	HO-RE	
1	STRCA	0.0773	0.1300	0.1304	0.1252	0.0823	0.1414	0.1144
	CNN	0.0643	0.0904	0.0777	0.0949	0.0966	0.0789	**0.0838**
	FBTRCA	0.0614	0.0939	0.0586	0.0949	0.0972	0.1033	0.0849
2	STRCA	0.0675	0.0738	0.0966	0.1160	0.1430	0.1317	0.1047
	CNN	0.1080	0.0738	0.1135	0.0949	0.1563	0.1101	0.1094
	FBTRCA	0.0316	0.0516	0.0816	0.0707	0.1033	0.1160	**0.0758**
3	STRCA	0.0766	0.0686	0.1633	0.1075	0.1488	0.1135	0.1130
	CNN	0.0589	0.0000	0.0943	0.1197	0.1118	0.0949	**0.0799**
	FBTRCA	0.0708	0.0000	0.0943	0.1197	0.1246	0.0943	0.0839
4	STRCA	0.0479	0.0939	0.0516	0.1476	0.1342	0.1449	0.1033
	CNN	0.0439	0.0636	0.0000	0.1229	0.1054	0.1350	0.0785
	FBTRCA	0.0287	0.0767	0.0000	0.1059	0.0575	0.1874	**0.0760**
5	STRCA	0.1071	0.0699	0.1900	0.1633	0.1174	0.1578	0.1343
	CNN	0.1359	0.0699	0.1317	0.1135	0.0949	0.0994	**0.1075**
	FBTRCA	0.0963	0.0422	0.1370	0.1370	0.0994	0.1729	0.1141
6	STRCA	0.0351	0.0351	0.1684	0.0973	0.1138	0.1450	0.0991
	CNN	0.0000	0.0000	0.0767	0.0876	0.0614	0.1227	**0.0581**
	FBTRCA	0.0264	0.0000	0.0636	0.0907	0.0939	0.1054	0.0633
7	STRCA	0.0998	0.1128	0.1359	0.1408	0.1488	0.1545	0.1321
	CNN	0.0791	0.0791	0.1557	0.1197	0.1437	0.1359	0.1188
	FBTRCA	0.0562	0.0966	0.1606	0.1246	0.1437	0.0835	**0.1109**
8	STRCA	0.0403	0.0583	0.0439	0.1088	0.0878	0.1246	0.0773
	CNN	0.0000	0.0351	0.0904	0.0878	0.0575	0.0643	**0.0559**
	FBTRCA	0.0264	0.0351	0.0469	0.0767	0.0904	0.0767	0.0587
9	STRCA	0.1097	0.0896	0.1497	0.1533	0.1485	0.1512	0.1337
	CNN	0.0403	0.0562	0.1717	0.1858	0.1629	0.0773	0.1157
	FBTRCA	0.0351	0.0562	0.1054	0.1385	0.1289	0.1118	**0.0960**
10	STRCA	0.0796	0.0963	0.1595	0.1434	0.1197	0.1160	0.1191
	CNN	0.0717	0.0614	0.1054	0.1649	0.0876	0.1160	0.1011
	FBTRCA	0.0748	0.0469	0.1033	0.1372	0.0707	0.0994	**0.0887**
11	STRCA	0.0919	0.1350	0.1494	0.1366	0.1418	0.2273	0.1470
	CNN	0.0994	0.0919	0.1033	0.1171	0.1354	0.1135	0.1101
	FBTRCA	0.0675	0.0675	0.0699	0.1148	0.1265	0.1174	**0.0939**
12	STRCA	0.1032	0.0823	0.1304	0.1048	0.1370	0.1703	0.1213
	CNN	0.0606	0.0667	0.1148	0.1261	0.0527	0.2000	0.1035
	FBTRCA	0.0469	0.0632	0.1171	0.0876	0.1075	0.1776	**0.1000**
13	STRCA	0.0615	0.0829	0.1289	0.1300	0.1359	0.0963	0.1059
	CNN	0.0439	0.0403	0.1385	0.1303	0.0878	0.1138	0.0924
	FBTRCA	0.0403	0.0430	0.1138	0.0835	0.0958	0.1227	**0.0832**
14	STRCA	0.0703	0.0766	0.1636	0.1333	0.1472	0.0767	0.1113
	CNN	0.0351	0.0351	0.0949	0.0994	0.0748	0.0958	**0.0725**
	FBTRCA	0.0351	0.0403	0.1059	0.1075	0.0671	0.0862	0.0737
15	STRCA	0.0904	0.0556	0.1229	0.1512	0.1067	0.1134	0.1067
	CNN	0.0439	0.0430	0.1135	0.1000	0.1216	0.1088	0.0885
	FBTRCA	0.0383	0.0430	0.0843	0.0748	0.0748	0.0878	**0.0672**
Average	STRCA	0.0772	0.0840	0.1323	0.1306	0.1275	0.1376	0.1149
	CNN	0.0590	0.0538	0.1055	0.1177	0.1034	**0.1111**	0.0917
	FBTRCA	**0.0491**	**0.0504**	**0.0895**	**0.1043**	**0.0988**	0.1162	**0.0847**

Table 12. Mean of Classification Accuracies of Dataset II Across Ten Folds (Movement vs Movement)

Subject	Method	Motion Pair										Average
		SU-PR	SU-HO	SU-PG	SU-LG	PR-HO	PR-PG	PR-LG	HO-PG	HO-LG	PG-LG	
1	STRCA	0.6000	0.5571	0.6429	0.5286	0.5857	0.6286	0.5857	0.6000	0.5929	0.5929	0.5914
	CNN	0.5357	0.7071	0.6286	0.5857	0.6000	0.6000	0.6000	0.6429	0.6571	0.5429	0.6100
	FBTRCA	0.4929	0.6571	0.6643	0.6143	0.6429	0.6571	0.6071	0.6643	0.6429	0.5857	**0.6229**
2	STRCA	0.5571	0.6571	0.6500	0.7286	0.5714	0.7071	0.6214	0.5714	0.5786	0.5143	0.6157
	CNN	0.5500	0.6571	0.6286	0.7714	0.6714	0.7071	0.6857	0.5571	0.5571	0.5286	0.6314
	FBTRCA	0.5643	0.7000	0.6929	0.7000	0.6429	0.7071	0.7000	0.6500	0.6643	0.5143	**0.6536**
3	STRCA	0.5071	0.5857	0.7000	0.6786	0.6286	0.6571	0.6214	0.5786	0.5500	0.6071	0.6114
	CNN	0.5643	0.6500	0.7214	0.7286	0.6429	0.7143	0.6786	0.6500	0.6071	0.6143	0.6571
	FBTRCA	0.5857	0.7571	0.7500	0.6929	0.6643	0.7357	0.6929	0.6500	0.6500	0.6714	**0.6850**
4	STRCA	0.6214	0.7571	0.7786	0.8214	0.7071	0.7571	0.7643	0.6786	0.7357	0.6214	0.7243
	CNN	0.6643	0.8143	0.8143	0.8214	0.7714	0.8143	0.8214	0.7357	0.7500	0.6786	0.7686
	FBTRCA	0.6571	0.8500	0.8429	0.8929	0.8286	0.8214	0.8429	0.7143	0.7786	0.7286	**0.7957**
5	STRCA	0.7286	0.6143	0.7571	0.7214	0.7214	0.7357	0.8143	0.7286	0.6929	0.6357	0.7150
	CNN	0.7071	0.6929	0.7714	0.8000	0.6929	0.7643	0.8643	0.6929	0.6571	0.6357	0.7279
	FBTRCA	0.7357	0.6786	0.8071	0.7429	0.7571	0.7929	0.8214	0.7429	0.6857	0.6643	**0.7429**
6	STRCA	0.5571	0.5857	0.8143	0.7143	0.5357	0.6929	0.7143	0.7929	0.6500	0.6500	0.6707
	CNN	0.5643	0.5786	0.7714	0.7429	0.6071	0.7214	0.6357	0.8214	0.7143	0.6500	0.6807
	FBTRCA	0.6071	0.5500	0.8214	0.7429	0.6143	0.7929	0.6857	0.7929	0.6786	0.7000	**0.6986**
7	STRCA	0.5500	0.5000	0.5357	0.5571	0.5143	0.5429	0.5357	0.5214	0.5429	0.4500	0.5250
	CNN	0.5500	0.5429	0.4929	0.5786	0.5643	0.5429	0.5643	0.5571	0.6214	0.5071	0.5521
	FBTRCA	0.5929	0.5286	0.5357	0.6000	0.6000	0.5571	0.5143	0.5929	0.5571	0.5643	**0.5643**
8	STRCA	0.6357	0.7214	0.6214	0.6857	0.6500	0.5643	0.6143	0.5714	0.6429	0.5929	0.6300
	CNN	0.5714	0.7286	0.6929	0.7071	0.6786	0.5714	0.6357	0.6429	0.6714	0.5357	0.6436
	FBTRCA	0.6500	0.7643	0.6929	0.7786	0.7643	0.6500	0.6857	0.7143	0.6857	0.5643	**0.6950**
9	STRCA	0.6143	0.5286	0.7071	0.7000	0.6214	0.7000	0.7571	0.6429	0.6000	0.6357	0.6507
	CNN	0.6643	0.5357	0.6857	0.6500	0.6500	0.7571	0.7286	0.6786	0.7143	0.6643	0.6729
	FBTRCA	0.6500	0.6071	0.7571	0.6357	0.6643	0.7429	0.7929	0.6500	0.6571	0.6714	**0.6829**
Average	STRCA	0.5968	0.6119	0.6897	0.6817	0.6151	0.6651	0.6698	0.6317	0.6206	0.5889	0.6371
	CNN	0.5968	0.6563	0.6897	0.7095	0.6532	0.6881	0.6905	0.6643	0.6611	0.5952	0.6605
	FBTRCA	**0.6151**	**0.6770**	**0.7294**	**0.7111**	**0.6865**	**0.7175**	**0.7048**	**0.6857**	**0.6667**	**0.6294**	**0.6823**

Table 13. Deviation of Classification Accuracies of Dataset II Across Ten Folds (Movement vs Movement)

Subject	Method	Motion Pair										Average
		SU-PR	SU-HO	SU-PG	SU-LG	PR-HO	PR-PG	PR-LG	HO-PG	HO-LG	PG-LG	
1	STRCA	0.1075	0.0878	0.1260	0.1355	0.1157	0.2043	0.1338	0.1223	0.1431	0.1906	0.1367
	CNN	0.1271	0.1139	0.1054	0.1205	0.1313	0.1622	0.1127	0.1065	0.1107	0.1223	0.1213
	FBTRCA	0.1324	0.0999	0.1216	0.1075	0.1347	0.1338	0.0967	0.1169	0.0825	0.1460	**0.1172**
2	STRCA	0.1054	0.1421	0.0979	0.1205	0.0891	**0.1035**	0.0955	0.1782	0.1188	0.1536	**0.1205**
	CNN	0.1617	0.1536	0.0811	0.0878	0.1021	0.1235	0.1075	0.1608	0.1643	0.0768	0.1219
	FBTRCA	0.1139	0.1677	0.1216	0.0940	0.1429	0.1446	0.1251	0.1280	0.1216	0.1251	0.1285
3	STRCA	0.1035	0.1205	0.0878	0.1315	0.1460	0.1251	0.1119	0.1559	0.1262	0.1129	0.1221
	CNN	0.1188	0.1280	0.0979	0.0811	0.1065	0.1388	0.1758	0.1324	0.1078	0.1021	**0.1189**
	FBTRCA	0.1338	0.1176	0.0907	0.1349	0.1119	0.1067	0.1306	0.1088	0.1595	0.1223	0.1217
4	STRCA	0.0757	0.1223	0.0979	0.0907	0.1407	0.0838	0.1169	0.1078	0.1013	0.1067	**0.1044**
	CNN	0.0828	0.1075	0.0904	0.1271	0.1677	0.1075	0.1129	0.0894	0.0694	0.1024	0.1057
	FBTRCA	0.0878	0.1366	0.0738	0.0907	0.0904	0.1024	0.0999	0.1214	0.0786	0.0563	0.0938
5	STRCA	0.0999	0.1127	0.1550	0.1485	0.0979	0.0894	0.0768	0.0999	0.1013	0.1280	**0.1109**
	CNN	0.0855	0.0894	0.0878	0.1608	0.1262	0.1216	0.0855	0.1349	0.1205	0.1235	0.1136
	FBTRCA	0.1119	0.1438	0.0678	0.1513	0.1436	0.1088	0.0772	0.0838	0.1436	0.1651	0.1197
6	STRCA	0.1251	0.1205	0.1513	0.1010	0.1852	0.0828	0.1010	0.0855	0.1280	0.1139	0.1194
	CNN	0.0855	0.1088	0.1107	0.1223	0.1552	0.1188	0.1366	0.1315	0.1166	0.0919	**0.1178**
	FBTRCA	0.1357	0.1169	0.1129	0.1075	0.1475	0.1280	0.1127	0.1324	0.1129	0.1380	0.1245
7	STRCA	0.1719	0.1117	0.1271	0.1338	0.1460	0.1176	0.1357	0.1431	0.1587	0.1349	0.1380
	CNN	0.1508	0.1313	0.1324	0.1035	0.1324	0.1475	0.0919	0.1421	0.1216	0.1446	0.1298
	FBTRCA	0.1508	0.1313	0.0772	0.1550	0.0768	0.1107	0.1380	0.1067	0.0811	0.1139	**0.1141**
8	STRCA	0.1188	0.0979	0.1169	0.1355	0.0855	0.1595	0.0964	0.1166	0.1214	0.1013	**0.1150**
	CNN	0.0891	0.1157	0.1169	0.1088	0.1271	0.1388	0.1631	0.1429	0.0602	0.1129	0.1176
	FBTRCA	0.1407	0.1067	0.0828	0.1366	0.1169	0.1559	0.1223	0.1065	0.1355	0.1280	0.1232
9	STRCA	0.1313	0.1269	0.1324	0.1572	0.1651	0.0738	0.1127	0.1468	0.1355	0.1235	0.1305
	CNN	0.1390	0.1357	0.1756	0.1595	0.1139	0.1223	0.0999	0.1725	0.1166	0.0955	0.1331
	FBTRCA	0.1366	0.1024	0.1176	0.1665	0.1349	0.0904	0.0919	0.1280	0.0999	0.0690	**0.1137**
Average	STRCA	**0.1154**	**0.1158**	0.1214	0.1282	0.1301	**0.1155**	**0.1090**	0.1285	0.1260	0.1295	0.1220
	CNN	0.1156	0.1204	0.1109	**0.1191**	0.1292	0.1312	0.1207	0.1348	**0.1098**	**0.1080**	0.1200
	FBTRCA	0.1271	0.1248	**0.0962**	0.1271	**0.1222**	0.1202	0.1105	**0.1147**	0.1128	0.1182	**0.1174**

Table 14. Mean of Classification Accuracies of Dataset II Across Ten Folds (Movement vs Resting)

Subject	Method	Motion Pair					Average
		SU-RE	PR-RE	HO-RE	PG-RE	LG-RE	
1	STRCA	0.7143	0.7643	0.8071	0.7214	0.6857	0.7386
	CNN	0.7929	0.7643	0.8214	0.7643	0.7357	0.7757
	FBTRCA	0.8571	0.8000	0.8071	0.8000	0.7643	**0.8057**
2	STRCA	0.9571	0.9357	0.9000	0.9071	0.8643	0.9129
	CNN	0.9429	0.9500	0.9214	0.8929	0.9071	0.9229
	FBTRCA	0.9571	0.9571	0.9357	0.9286	0.9286	**0.9414**
3	STRCA	0.8214	0.8571	0.7571	0.7500	0.7143	0.7800
	CNN	0.8000	0.8786	0.8357	0.8571	0.8429	0.8429
	FBTRCA	0.8714	0.9000	0.9071	0.8571	0.7857	**0.8643**
4	STRCA	0.9286	0.9286	0.9071	0.8857	0.8786	0.9057
	CNN	0.9500	0.9500	0.9286	0.9000	0.9214	0.9300
	FBTRCA	0.9786	0.9429	0.9214	0.9286	0.9286	**0.9400**
5	STRCA	0.8571	0.8643	0.8429	0.7786	0.8214	0.8329
	CNN	0.8929	0.9000	0.8571	0.8643	0.8500	0.8729
	FBTRCA	0.8929	0.9143	0.8929	0.8786	0.8857	**0.8929**
6	STRCA	0.8571	0.8786	0.8714	0.8571	0.8071	0.8543
	CNN	0.8714	0.8929	0.9357	0.8643	0.7857	0.8700
	FBTRCA	0.8357	0.9000	0.9214	0.9071	0.7929	**0.8714**
7	STRCA	0.6214	0.6357	0.6786	0.5857	0.6429	0.6329
	CNN	0.7786	0.7643	0.7214	0.6643	0.6857	0.7229
	FBTRCA	0.7357	0.7286	0.7643	0.7000	0.7286	**0.7314**
8	STRCA	0.8000	0.7929	0.7643	0.7714	0.7500	0.7757
	CNN	0.8286	0.8357	0.8571	0.7500	0.7929	0.8129
	FBTRCA	0.8714	0.8643	0.8429	0.7714	0.8000	**0.8300**
9	STRCA	0.8786	0.8929	0.8000	0.6429	0.7429	0.7914
	CNN	0.8571	0.8714	0.8429	0.6643	0.7214	0.7914
	FBTRCA	0.8857	0.9000	0.8429	0.7071	0.7643	**0.8200**
Average	STRCA	0.9124	0.9175	0.8219	0.7446	0.7672	0.8327
	CNN	0.9553	0.9461	0.8864	0.8257	0.8423	0.8912
	FBTRCA	**0.9672**	**0.9589**	**0.9014**	**0.8364**	**0.8558**	**0.9039**

Table 15. Deviation of Classification Accuracies of Dataset II Across Ten Folds (Movement vs Resting)

Subject	Method	Motion Pair					Average
		SU-RE	PR-RE	HO-RE	PG-RE	LG-RE	
1	STRCA	0.0952	0.0955	0.1508	0.0979	0.0964	0.1072
	CNN	0.1235	0.0757	0.0772	0.1067	0.1013	0.0969
	FBTRCA	0.0673	0.0999	0.1013	0.0999	0.1119	**0.0961**
2	STRCA	0.0602	0.0527	0.0602	0.0678	0.1139	0.0710
	CNN	0.0452	0.0588	0.0625	0.0842	0.1067	0.0715
	FBTRCA	0.0369	0.0499	0.0527	0.0476	0.0476	**0.0470**
3	STRCA	0.0772	0.0825	0.1127	0.1271	0.1347	0.1068
	CNN	0.0940	0.0482	0.1119	0.1260	0.1205	0.1001
	FBTRCA	0.0940	0.0369	0.1067	0.1010	0.0476	**0.0773**
4	STRCA	0.0952	0.0583	0.1013	0.0904	0.0894	0.0869
	CNN	0.0955	0.0588	0.0673	0.0768	0.0710	0.0739
	FBTRCA	0.0482	0.0563	0.0710	0.0583	0.0753	**0.0618**
5	STRCA	0.0753	0.0855	0.1054	0.1139	0.0967	0.0954
	CNN	0.0607	0.0964	0.1010	0.0855	0.0855	**0.0858**
	FBTRCA	0.0772	0.0940	0.0772	0.0894	0.1021	0.0880
6	STRCA	0.0952	0.0678	0.1054	0.1010	0.1431	0.1025
	CNN	0.0452	0.0842	0.0625	0.0786	0.1117	**0.0764**
	FBTRCA	0.1013	0.1021	0.0855	0.0757	0.1188	0.0967
7	STRCA	0.1545	0.1523	0.1179	0.0738	0.1506	**0.1298**
	CNN	0.1665	0.0955	0.1407	0.1470	0.1396	0.1379
	FBTRCA	0.1719	0.1710	0.1119	0.0999	0.1421	0.1394
8	STRCA	0.1054	0.0710	0.0828	0.1608	0.1226	0.1085
	CNN	0.1313	0.0828	0.0891	0.0967	0.0710	0.0942
	FBTRCA	0.1107	0.0625	0.0878	0.1205	0.0878	**0.0939**
9	STRCA	0.0678	0.0842	0.1054	0.1117	0.1223	0.0983
	CNN	0.0825	0.1157	0.0811	0.1349	0.1699	0.1168
	FBTRCA	0.0602	0.0838	0.0738	0.1407	0.1013	**0.0920**
Average	STRCA	0.0918	0.0833	0.1047	0.1049	0.1189	0.1007
	CNN	0.0938	**0.0796**	0.0882	0.1040	0.1086	0.0948
	FBTRCA	**0.0853**	0.0841	**0.0853**	**0.0925**	**0.0927**	**0.0880**

Table 16. P-value between STRCA and FBTRCA calculated by two-side t-test (Dataset I-RP)

Motion	Subject															Average
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
EF-EE	0.8093	0.6415	0.3785	0.2014	0.0586	0.2806	0.4291	0.8244	0.8923	0.6945	0.4803	0.5653	0.1221	0.0723	1.0000	0.4967
EF-SU	0.2434	0.8720	0.6809	**0.0102**	0.3955	0.5256	0.4762	0.6485	0.9113	0.3812	0.2564	0.7364	0.7517	0.5872	0.6585	0.5423
EF-PR	**0.0142**	0.2285	0.1558	**0.0499**	0.8885	0.7486	0.3082	0.8163	0.8789	0.6733	0.3553	0.1955	0.2388	**0.0186**	0.4697	0.4027
EF-HC	0.2317	0.6445	0.7486	0.5469	0.6103	0.5914	0.7331	0.4545	1.0000	0.6631	0.4351	1.0000	**0.0750**	**0.0170**	0.6215	0.5582
EF-HO	0.6556	0.9036	0.2691	0.1422	0.1127	0.8890	**0.0489**	0.3618	1.0000	0.4746	0.8859	0.1047	0.5530	0.2557	0.7776	0.4956
EE-SU	**0.0023**	0.1879	0.1672	0.2962	0.3860	0.2912	0.5560	0.5362	0.5872	0.6432	0.7486	0.8437	0.1041	0.6215	0.6601	0.4421
EE-PR	**0.0019**	0.2809	**0.0161**	0.7031	0.5843	0.8409	0.4700	0.6713	0.3630	1.0000	**0.0126**	0.5402	0.5452	0.3220	0.5427	0.4596
EE-HC	0.8070	0.7187	0.8279	0.1401	0.3419	0.7992	0.8914	0.1201	0.3606	**0.0838**	0.2778	0.5759	0.6085	0.5979	0.4419	0.5062
EE-HO	0.7851	0.1068	0.3125	0.1515	0.8020	0.7007	0.3140	**0.0860**	0.7771	0.7756	0.6601	0.3219	0.3388	0.6300	0.8569	0.5079
SU-PR	0.8837	0.4410	0.7618	0.1825	0.2068	0.5979	0.7805	0.8093	1.0000	0.9161	0.3045	0.2962	0.4393	0.2649	0.8984	0.5855
SU-HC	0.8569	0.8535	0.7869	0.0277	0.4017	0.6237	0.7160	0.8558	0.8323	0.2540	0.3913	1.0000	0.4246	0.4077	0.6278	0.6040
SU-HO	0.1558	0.3924	0.4218	0.2257	0.1929	1.0000	0.8697	0.5025	0.7507	0.9003	0.9030	0.6809	0.7521	0.8536	0.4872	0.6059
PR-HC	0.5001	0.7587	1.0000	0.7272	0.4391	0.1145	0.4311	0.6432	0.8120	0.8977	0.8536	0.0739	0.8973	0.5470	0.5520	0.6165
PR-HO	0.8558	1.0000	0.6733	0.6126	0.1346	0.7486	0.8832	0.4915	0.7606	1.0000	0.7911	0.4246	0.4700	0.3760	0.7756	0.6665
HC-HO	0.5025	1.0000	0.6837	0.1356	0.7033	0.8837	0.7450	0.5069	0.7606	0.3388	0.8837	0.7676	0.6893	0.6839	0.3419	0.6418
EF-RE	0.2743	0.3581	0.3760	0.4645	0.1513	1.0000	0.8558	0.0145	0.2878	0.5305	0.1150	0.1589	0.1964	0.8379	0.4453	0.4044
EE-RE	0.6182	0.1753	**0.0062**	0.6652	0.1769	0.7142	0.6565	0.6601	0.3077	0.7730	0.3581	0.5872	0.6837	0.5165	0.6733	0.5048
SU-RE	0.1892	0.1194	0.2546	0.6132	0.3765	0.8086	1.0000	0.3177	0.6164	0.4313	0.2895	0.4987	0.5241	0.4973	0.7120	0.4832
PR-RE	0.2030	0.3955	0.8681	0.8201	1.0000	1.0000	0.5452	0.4163	0.3018	0.0594	0.0247	0.3306	0.0179	0.2846	0.6733	0.4627
HC-RE	0.4206	0.4228	0.2945	0.8297	0.2564	1.0000	0.6215	0.4073	0.0166	0.8437	0.7372	0.0913	0.5510	0.5872	0.4925	0.5048
HO-RE	0.3388	0.2134	0.2963	1.0000	0.8770	0.5628	0.1515	0.6906	0.1785	0.4291	0.1201	0.1302	0.2163	0.3860	1.0000	0.4394
Average	0.4452	0.5102	0.4752	0.4069	0.4332	0.7010	0.5944	0.5159	0.6379	0.6078	0.4707	0.4725	0.4381	0.4459	0.6528	0.5205

Table 17. P-value between STRCA and FBTRCA calculated by two-side t-test (Dataset I-RP+MMP)

Motion	Subject															Average
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
EF-EE	0.3661	0.3858	0.0082	0.2139	1.0000	0.1291	0.4543	0.5530	**0.0008**	0.6278	0.6578	**0.0379**	0.8010	**0.0835**	0.3471	0.3778
EF-SU	0.4391	0.3180	**0.0225**	0.1221	0.5530	0.1387	0.4721	**0.0747**	0.6733	0.2507	0.4218	0.6862	0.6753	**0.0913**	0.8003	0.3826
EF-PR	**0.0838**	0.1597	**0.0739**	0.4697	**0.0687**	0.1964	**0.0490**	**0.0499**	**0.0320**	0.3433	**0.0750**	**0.0046**	**0.0329**	0.2675	**0.0041**	0.1274
EF-HC	**0.0676**	0.7264	**0.0024**	0.1294	**0.0266**	0.6394	0.4123	0.6319	0.2095	1.0000	0.2883	0.3750	**0.0087**	0.1184	0.7007	0.3558
EF-HO	**0.0382**	0.4825	**0.0086**	0.1929	0.2546	0.4376	1.0000	0.1869	0.3741	**0.0782**	0.1346	0.1597	**0.0155**	**0.0021**	0.2011	0.2378
EE-SU	0.1433	0.3760	**0.0104**	0.1615	0.7287	0.2564	0.6900	0.2434	0.1184	0.5456	0.5874	0.5944	0.1268	0.6278	0.7507	0.3974
EE-PR	**0.0021**	0.2208	0.1030	0.1964	0.1589	0.7486	0.5120	0.2468	**0.0083**	**0.0587**	0.1468	**0.0439**	**0.0382**	**0.0082**	0.4118	0.1936
EE-HC	**0.0579**	1.0000	0.4240	0.1145	0.8451	0.5049	0.7231	0.3579	0.5197	0.1194	0.2853	0.2986	0.2069	0.5165	0.6468	0.4414
EE-HO	**0.0208**	0.1194	**0.0172**	**0.0925**	0.5843	0.3581	0.8820	**0.0586**	0.1116	1.0000	0.3219	**0.0525**	0.7886	**0.0056**	0.4474	0.3240
SU-PR	0.1422	0.6991	**0.0943**	**0.0131**	0.4474	0.6005	0.5402	**0.0626**	0.7873	0.9132	1.0000	**0.0026**	0.6961	0.1150	0.3349	0.4299
SU-HC	0.1828	0.2643	**0.0381**	**0.0340**	0.4247	0.1820	0.6864	0.4419	0.5197	**0.0652**	1.0000	0.1069	0.1356	0.3968	1.0000	0.3652
SU-HO	**0.0126**	0.5803	0.1597	**0.0531**	0.2650	0.5172	0.7886	0.7771	**0.0410**	0.7606	0.1580	**0.0114**	0.1206	0.8061	0.8609	0.3942
PR-HC	0.8705	0.3263	0.2163	0.8808	1.0000	0.8086	0.4075	0.4697	0.8875	0.8802	0.8180	0.4351	0.8756	0.6195	1.0000	0.6997
PR-HO	0.1785	0.2295	0.4486	0.1707	0.4077	0.8020	1.0000	0.4286	0.2758	0.2188	0.7313	0.2188	0.2557	0.1150	0.6924	0.4116
HC-HO	0.8957	0.2858	0.2593	0.3760	0.7486	0.7873	1.0000	1.0000	0.3750	0.4474	**0.0838**	0.7559	0.4822	0.9052	0.2095	0.5741
EF-RE	**0.0026**	**0.0203**	0.4583	**0.0544**	0.1278	0.5560	**0.0129**	0.2878	**0.0345**	0.3065	**0.0069**	0.6182	**0.0453**	0.1964	**0.0553**	0.1855
EE-RE	0.1686	0.3061	**0.0150**	0.3553	0.1387	0.1510	0.7269	0.4486	**0.0134**	0.4313	**0.0756**	0.7642	0.1753	0.1451	**0.0372**	0.2635
SU-RE	**0.0401**	0.3306	0.1108	**0.0017**	0.4286	**0.0525**	0.4230	0.6601	**0.0156**	**0.0838**	0.5724	0.4331	0.1118	0.1221	**0.0203**	0.2271
PR-RE	**0.0114**	**0.0789**	**0.0199**	0.1346	0.1985	0.7947	0.2986	0.2945	0.2266	0.1285	0.2527	**0.0544**	**0.0007**	**0.0187**	0.1897	0.1801
HC-RE	**0.0624**	0.4825	0.3858	**0.0645**	0.1673	**0.0965**	0.7842	0.1278	**0.0035**	**0.0051**	**0.0442**	0.2199	0.2418	0.2295	**0.0015**	0.1944
HO-RE	**0.0439**	0.3794	0.1036	0.3624	0.3568	0.3487	0.2069	0.3388	**0.0623**	0.2301	**0.0305**	**0.0424**	0.1145	**0.0378**	0.2447	0.1935
Average	0.1824	0.3701	0.1419	0.1997	0.4253	0.4336	0.5748	0.3686	0.2519	0.4045	0.3663	0.2817	0.2833	0.2585	0.4265	0.3313

Table 18. P-value between STRCA and FBTRCA calculated by two-side t-test (Dataset II)

Motion	Subject									Average
	1	2	3	4	5	6	7	8	9	
SU-PR	**0.0624**	0.8859	0.1592	0.3428	0.8820	0.4029	0.5607	0.8090	0.5585	0.5182
SU-HO	**0.0287**	0.5452	0.0047	0.1267	0.2806	0.5096	0.6065	0.3618	0.1449	0.2899
SU-PG	0.7033	0.3968	0.2263	0.1145	0.3624	0.9061	1.0000	0.1323	0.3836	0.4695
SU-LG	0.1346	0.5617	0.8132	**0.0951**	0.7530	0.5480	0.5165	0.1443	0.3864	0.4392
PR-HO	0.3222	0.1964	0.5470	**0.0338**	0.5241	0.3079	0.1177	**0.0225**	0.5330	0.2894
PR-PG	0.7157	1.0000	0.1482	0.1419	0.2158	**0.0527**	0.7829	0.2401	0.2605	0.3953
PR-LG	0.6864	0.1318	0.2057	0.1235	0.8379	0.5579	0.7304	0.1642	0.4474	0.4317
HO-PG	0.2451	0.2723	0.2504	0.4956	0.7331	1.0000	0.2218	**0.0104**	0.9089	0.4597
HO-LG	0.3510	0.1283	0.1375	0.3045	0.8992	0.6031	0.8027	0.4660	0.2973	0.4433
PG-LG	0.9261	1.0000	0.2378	0.0117	0.6706	0.3886	0.0556	0.5867	0.4351	0.4791
SU-RE	**0.0011**	1.0000	0.2100	0.1558	0.3087	0.6319	0.1352	0.1567	0.8061	0.3784
PR-RE	0.4246	0.3630	0.1510	0.5843	0.2295	0.5872	0.2160	**0.0282**	0.8513	0.3817
HO-RE	1.0000	0.1753	**0.0068**	0.7193	0.2418	0.2593	0.1127	**0.0543**	0.3061	0.3195
PG-RE	**0.0925**	0.4240	**0.0514**	0.2237	0.0425	0.2263	**0.0093**	1.0000	0.2725	0.2602
LG-RE	0.1099	0.1171	0.1313	0.1929	0.1656	0.8108	0.2069	0.3082	0.6747	0.3019
Average	0.3869	0.4799	0.2187	0.2444	0.4764	0.5195	0.4050	0.2990	0.4844	0.3905

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