Towards Multi-class Pre-movement Classification

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Abstract—In non-invasive brain-computer interface systems, pre-movement decoding plays an important role in the detection of movement before limbs actually move. Movement-related cortical potential is a kind of brain activity associated with pre-movement decoding. In current studies, patterns decoded from movement are mainly applied to the binary classification between movement state and resting state, such as elbow flexion and rest. The classifications between two movement states and among multiple movement states are still challenging. This study proposes a new method, the star-arrangement spectral filtering (SASF), to solve the multi-class pre-movement classification problem. We first design a referenced task-related component analysis (RTRCA) framework that consists of two modules. This first module is the classification between movement state and resting state; the second module is the classification of multiple movement states. SASF is developed by optimizing the features in RTRCA. In SASF, feature selection on filter banks is used on the first module of RTRCA, and feature selection on time windows is used on the second module of RTRCA. A linear discriminant analysis classifier is used to classify the optimized features. In the binary classification between two motions, the classification accuracy of SASF achieves $0.9670\pm0.0522$, which is significantly higher than the result provided by the deep convolutional neural network ($0.6247\pm0.0680$) and the discriminative spatial pattern method ($0.4400\pm0.0700$). In the multi-class classification of 7 states, the classification accuracy of SASF is $0.9491\pm0.0372$. The proposed SASF greatly improves the classification between two motions and enables the classification among multiple motions. The result shows that the movement can be decoded from EEG signals before the actual limb movement.

Keywords—Movement-Related Cortical Potential, Binary and Multi-Class Pre-movement Classification, Movement Intention Detection, Task-Related Component Analysis, Feature Selection.

I. INTRODUCTION

Non-invasive brain-computer interface is a framework that bridges the gap between human brains and external computers [1]. Electroencephalograms (EEGs) are biological signals acquired from human scalps with a brain-computer interface system [2]. EEG signals are usually used to generate multiple commands by classifying certain tasks, such as the left and right limb movements, or multiple visual stimuli [3]–[7]. These commands can be used to control robots or other external devices [8]. However, the control commands in brain-computer are not practical. In motor imagery, the commands are generated by the classification on movements of left and right limbs. These commands are controlled by human intention, which are active-evoked commands. However, because motor imagery is a binary classification task, the number of commands is limited to two. In steady-state visual evoked potential, the number of commands depends on the number of visual stimuli. Hence there are more control commands. However, steady-state visual evoked potential is evoked by external visual stimuli and is not under the control of human intention. The commands in steady-state visual evoked potential are passive-evoked commands. The passive-evoked commands limit the usage of steady-state visual evoked potential. Most studies on brain-computer interface focuses on the improvement of existing classification tasks in motor imagery and steady-state visual evoked potential. The exploration on more user-friendly brain activities is ignored [9]–[14]. The limb movement is an active-evoked action which is controlled by human’s own intention. The classification of multiple movement states is more friendly to users than visual stimuli and has more commands than the classification of left and right limbs. However, there is no method for the multi-class movement classification. To the authors’ knowledge, this work proposes the first method used in the classification of multiple movement states.

Movement-related cortical potential (MRCP) is one of the brain activities that can be detected from EEG signals before the actual movement of limbs occur [15]–[17]. Patterns decoded before the actual movement can help all those subjects who can plan the movement but are unable to execute it. Therefore, MRCP analysis plays an important role in pre-movement detection. In MRCP analysis, the limb begins to move at the movement onset. During the following one second, limb movement can be observed and monitored. This one-second time window is called the Movement Monitoring Potential (MMP) section. The time window, which is located two seconds before movement onset, is the readiness potential (RP) section. The pre-movement patterns decoded from 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 movement states shows an increase followed by a rapid decrease around movement onset in comparison to the relatively steady grand average MRCP of the resting state.
In previous studies on binary classification between movement state and resting state with MRCP signals, Ofner et al. proposed the discriminative spatial pattern (DSP) method [18]. This method allows the calculation of a linear discriminant analysis (LDA) classifier for every time step. By analysing the classification accuracy for every step, it shows that the accuracies increase as the time point approaches the movement onset in both the RP and MMP sections. Jeong et al. proposed the subject-dependent and section-wise spectral filtering (SSSF) method [19]. This method utilizes the mean amplitude of MRCP signals in both RP and MMP sections as pre-movement patterns. In grand average MRCP, the amplitudes of signals are distinct between the movement state and resting state. Therefore, SSSF can classify the signals in the movement state and resting state. However, it ignores the increasing trend or decreasing trend of grand average MRCP and thus cannot achieve better performance. Duan et al. proposed a pre-movement pattern decoding method, standard task-related component analysis (STRCA) [20]. This method has a concise structure, which consists of both the spatial filter task-related component analysis (TRCA) and the features canonical correlation patterns (CCPs). STRCA achieves state of the art classification performance when decoding pre-movement patterns in the RP section. The filter bank TRCA (FB-TRCA) proposed by Jia et al. develops the STRCA method by incorporating the filter bank technique [21]. In comparison to STRCA, FB-TRCA achieves a significantly improved result in the classification between movement and resting states. The CCPs in both STRCA and FB-TRCA are used to measure the similarity between the unlabeled trials and the grand average MRCP. Therefore, the increasing trend in the RP section is transformed into pre-movement patterns, which enables STRCA and FB-TRCA to achieve better performance than SSSF. However, the similarity measured by STRCA or FB-TRCA covers the whole RP section, which refers to the overall similarity but ignores how the similarity changes in the RP section. The deep learning-based technique of the deep convolutional neural network (DCNN), proposed by Mammone et al., achieves a high classification accuracy but the structure of the DCNN makes it difficult to explain how the pre-movement patterns are extracted [22].

In the studies on multi-class pre-movement classification, the DSP method proposed by Ofner et al. can be used. However, this method is used to analyse how the accuracy changes in RP and MMP sections. The DCNN method proposed by Mammone et al. is also a method for the binary classification between two movements. In both the DSP and DCNN methods, the classification accuracies show that it is still difficult to distinguish the movement states in pre-movement decoding. In Table I, the classification results of each method are given.

**TABLE I**

| Method       | Movement vs Resting | Movement vs Movement |
|--------------|---------------------|----------------------|
| DSP [18]     | 0.8500±0.0500       | 0.4400±0.0700        |
| SSSF [19]    | 0.7300±0.0783       | -                    |
| STRCA [20]   | 0.8349±0.1110       | -                    |
| FB-TRCA [21] | 0.6700±0.1022       | -                    |
| DCNN [22]    | 0.9030±0.0560       | 0.6247±0.0070        |

The difficulties of multi-class pre-movement classification are located at the differences between movements. Ofner et al. pointed out that the amplitude and changing trend of grand average MRCP are different among movements [18], [23]. However, there is no such method that can seize the changing trend to distinguish different motions. In SSSF, the mean of signals is used as the features. In STRCA and FB-TRCA, the overall similarity in the RP section is used as the features. In comparison to the overall constant in SSSF and the overall similarity in STRCA or FB-TRCA, it is necessary to develop a new method that uses the changing trend as the features.

Except for the features for multi-class pre-movement classification, the framework is also unknown and remains to be developed. In previous studies on multi-class pre-movement classification, DCNN was equipped with a multi-layer neural network, and it was difficult to explain how the features were extracted. DSP has a concise framework, but the classification accuracies are not persuasive.

To develop a method for multi-class pre-movement classification, it is unavoidable to find (1) features indicating the changing trend of grand average MRCP and (2) a framework distinguishing the differences of multiple movements. Therefore, we propose the new multi-class pre-movement classification method with three steps:

1. Develop the referenced TRCA (RTRCA) framework for the classification between two motions;
2. Propose the time-constraint TRCA (TC-TRCA) method which utilizes the changing trend of grand average MRCP;
3. Propose the star-arrangement spectral filtering (SASF) method for multi-class pre-movement classification.

To ease the reading of this manuscript, the abbreviations appearing in it are listed in Table II.

In Section II, the public dataset used and the proposed SASF method are introduced. Section III gives the result analysis from three aspects. Then, we discuss how SASF works in Section IV. Finally, Section V concludes the work in this study.
II. MATERIAL AND METHOD

A. Dataset Description

The dataset used in this study is a public dataset [18]. Considering that the proposed SASF method is developed based on the STRCA method, the same EEG dataset and preprocessing procedure in STRCA are adopted when processing the EEG signals [20], [21]. The dataset consists of 15 subjects and 7 states, including the resting state (rest (RE)) and 6 movement states. The movement states consist of 6 limb motions, including supination (SU), pronation (PR), hand close (HC), hand open (HO), elbow flexion (EF) and elbow extension (EE). A g.tec device (medical engineer GmbH, Austria) is used to acquire EEG signals from 11 channels. The 11 channels include 5 electrodes in the center of the motor cortex and 6 electrodes in the surroundings of the motor cortex. According to the 10/20 international system, the 5 center electrodes are FCz, C3, Cz, C4, CPz and the 6 surrounding electrodes are F3, Fz, F4, P3, Pz and P4. In the settings of the EEG electrode placement, the right mastoid is set as the reference electrode. A 5DT GloVe sensor (5DT, USA). Considering the computation load and precision requirement in data processing, both EEG signals from 11 electrodes and movement trajectory $Hand_y$ are downsampled to 256 Hz.

In this dataset, the acquisition paradigm is trial-based. At the start time of a trial, beep sounds and a cross mark is displayed on the computer screen. Two seconds later, the computer screen displays a cue, which indicates the required motions (or rest). The subjects were asked to move their limbs or hands when the screen displayed the cue. For each motion, subjects repeat the paradigm 60 times. Because both hand trajectory and EEG signals are acquired simultaneously, the movement onset can be located precisely with the hand trajectory $Hand_y$.

When the hand trajectory $Hand_y$ is used to locate the movement onset, the 1-order difference of $Hand_y$ is taken to capture the changes of trajectory. Then a 1-order Savitzky-Golay finite impulse response smoothing filter is applied to the difference of $Hand_y$ to smooth the disturbance. Considering that the frame length of the smoothing filter will influence the location of the located movement onset, the frame length is set to 31 after a careful parameter tuning. For different motions, the following step of movement onset localization differs due to the amplitude differences of these motions.

In the two motions related to elbow movement, EF and EE have relatively higher amplitudes. In some trials, the trajectory

| Abbreviation | Full Name | Description |
|--------------|-----------|-------------|
| EEG          | Electroencephalogram | Multi-channel signals acquired from the surface of brain scalp. |
| MRCP         | Movement-Related Component Potential | A kind of brain activity related to pre-movement. |
| RP           | Readiness Potential | A stage located at two seconds before the movement onset. |
| MMP          | Movement Monitoring Potential | A stage located at one seconds after the movement onset. |
| SU           | Supination | A movement state of upper limb |
| PR           | Pronation  | A movement state of upper limb |
| HC           | Hand Close | A movement state of upper limb |
| HO           | Hand Open  | A movement state of upper limb |
| EF           | Elbow Flexion | A movement state of upper limb |
| EE           | Elbow Extension | A movement state of upper limb |
| DSP          | Discriminative Spatial Pattern | A binary classification method for movement and resting states [18]. |
| SSSF         | Subject-dependent and Section-wise Spectral Filtering | A binary classification method for movement and resting states [19]. |
| STRCA        | Standard Task-Related Component Analysis | A binary classification method for movement and resting states [20]. |
| RTRCA        | Referenced Task-Related Component Analysis | A binary classification method for movement and resting states [20]. |
| FB-TRCA      | Filter Bank Tasked-Related Component Analysis | A method that optimizes STRCA by filter bank selection [21]. |
| TC-TRCA      | Time-Constraint Tasked-Related Component Analysis | A method that optimizes STRCA by filter bank selection. |
| SASF         | Star-Arrangement Spectral Filtering | A multi-class classification method for multiple movement states. |
| TRCA         | Task-Related Component Analysis | The spatial filter used in STRCA [20]. |
| CCP          | Canonical Correlation Pattern | The features extracted in STRCA [20]. |
| MIQ          | Mutual Information Quotient | A feature selection method based on mutual information [24]. |
| MAXREL       | Maximum Relevance | A feature selection method based on mutual information [25]. |
| MINRED       | Minimum Redundancy | A feature selection method based on mutual information [25]. |
| MRMR         | Minimum Redundancy Maximum Relevance | A feature selection method based on mutual information [25]. |
| QPFS         | Quadratic Programming Feature Selection | A feature selection method based on mutual information [26]. |
| CIFE         | Conditional Infomax Feature Extraction | A feature selection method based on mutual information [27]. |
| CMIM         | Conditional Mutual Information Minimization | A feature selection method based on mutual information [28]. |
| MMRTR        | Maximum Relevance Minimum Total Redundancy | A feature selection method based on mutual information [29]. |
| SVM          | Support Vector Machine | A binary/multi-class classifier |
| LDA          | Linear Discriminant Analysis | A binary/multi-class classifier |

Note: The bold abbreviations indicate that this method is first proposed in this work.
Some trials are manually removed because movement contamination influences the localization of the movement onset. In the rest four motions related to hand movement, trajectory Hand is a lower amplitude and signal-noise ratio than limb movement. The noise in these motions is difficult to filter. Therefore, trial rejection with variance is disabled. After the maximum normalization, the function $f(x) = a \exp((-((x - b)/c)^2) + d)$ is used to approach the normalized signals by tuning the parameters $a$, $b$, $c$, $d$, where 'exp' is the exponential function. Trials are rejected if the normalized signals fulfill $a < 0.05$, $c > 100$, and $d > 10$. Then, a threshold criterion is applied to the exponential function to decide on the movement onset.

In the processing procedure of EEG signals in the resting state, the amplitude of Hand is steady. Therefore, the trials are rejected because the movement is hardly detected. The noise in these motions is difficult to filter.

Pre-movement patterns are extracted from EEG signals before the movement onset. With the movement onset or fake movement onset located above, the RP section and MMP before the movement onset. With the movement onset or fake movement onset located above, the RP section and MMP before the movement onset.

The linear sum of weighted EEG signals $X$ across channels is defined as $Y$:

$$Y_{i,j}^k = \sum_{i=1}^{N_c} w_{i,i,j}^k X_{i,j}, \quad j = 1, ..., N_l.$$

Covariance of all trial combinations are added up:

$$C_{j_1,j_2}^k = \sum_{j_1=1}^{N_l} C_{j_1,j_2}^k = \sum_{j_1=1}^{N_l} \text{Cov}(Y_{i,j_1}^k, Y_{i,j_2}^k)$$

$w_i^k$ is the weight for the EEG signals in channel $i$ of $k$th class. In TRCA, the task-related signal $s$ is recovered from $Y$. By maximizing the inter-trial covariance, the ideal solution can be approximated. The covariance $C_{j_2}^k$ between the $j_1$-th trial and the $j_2$-th trial can be obtained by:

$$C_{j_1,j_2}^k = \sum_{i_1,i_2} w_{i_1}^k w_{i_2}^k \text{Cov}(X_{i_1,j_1}, X_{i_2,j_2}).$$

The constrained spatial filter can be obtained by solving the generalized eigenvalue problem to maximize

$$J = \frac{w^T S^k w}{w^T Q^k w}$$

The spatial filter utilizes the eigenvectors with three maximum eigenvalues from two classes. By concatenating the eigenvectors two classes, the spatial filter of TRCA is generated.

**B. Referenced Task-Related Component Analysis**

1) **Standard Task-Related Component Analysis**: Standard task-related component analysis (STRCA) is used to classify the movement and resting state with MRCP signals in the RP section [20]. The STRCA method consists of a spatial filter and coefficient features. The EEG signals are first filtered by spatial filter task-related component analysis (TRCA). The canonical correlation pattern (CCP) features are then extracted from EEG signals. Finally, the linear discriminant analysis (LDA) classifier is applied to the extracted features. Figure 2 shows the structure of the STRCA method.

a) TRCA: TRCA is such a spatial filter that maximizes the reproducibility during the task, which was once used in the spatial filtering of visual-evoked potential (VEP) [30]. Duan et al. developed the idea that MRCP signals and VEP signals have similar mountain-shaped spatial distributions and thus incorporated the TRCA spatial filter into MRCP processing [20]. The training set of EEG signals is denoted as $X^k \in \mathbb{R}^{N_c \times N_r \times N_l}$ for two classes ($k = 1, 2$). In TRCA, it is assumed that the EEG signal $X^k$ is added up with two components. The two components include (1) task-related signal $s \in \mathbb{R}^{N_c \times 1}$ and (2) task-unrelated noise $n \in \mathbb{R}^{N_c \times 1}$. The relationship between $X$, $s$ and $n$ is described with a linear model:

$$X_{i,j}^k = a_{1,i,j}^k s_{i,j} + a_{2,i,j}^k n_{i,j},$$

$$i = 1, ..., N_c, \quad j = 1, ..., N_l.$$

The linear model of $s$ and $n$ is steady. Therefore, the $s$ and $n$ are similar mountain-shaped spatial distributions and thus incorporated the TRCA spatial filter into MRCP processing [20]. The training set of EEG signals is denoted as $X^k \in \mathbb{R}^{N_c \times N_r \times N_l}$ for two classes ($k = 1, 2$). In TRCA, it is assumed that the EEG signal $X^k$ is added up with two components. The two components include (1) task-related signal $s \in \mathbb{R}^{N_c \times 1}$ and (2) task-unrelated noise $n \in \mathbb{R}^{N_c \times 1}$. The relationship between $X$, $s$ and $n$ is described with a linear model:

$$X_{i,j}^k = a_{1,i,j}^k s_{i,j} + a_{2,i,j}^k n_{i,j},$$

$$i = 1, ..., N_c, \quad j = 1, ..., N_l.$$
In the RTRCA method, STRCA is first used as the classification method between the movement state and resting state. Feature extraction between the movement state and resting state is the first module of the RTRCA framework.

**Module 2:** In the RTRCA method, the CCP features of two STRCAs are then used to classify the two movement states. Thus, module 2 of the RTRCA framework serves for feature extraction between the movement state and movement state.

In the RTRCA method, the features in the two modules are both CCP features. The extracted features can be further optimized with feature selection.

### C. Optimized Standard Task-Related Component Analysis Methods

In the other brain activities that can be observed with EEG signals, optimization based on the time domain and frequency domain can greatly improve the classification performance [12], [14], [31]. For example, in motor imagery analysis, Zhang et al. proposed a temporal constraint sparse group spatial pattern, which optimizes the traditional common spatial pattern method with feature selection in the time domain and frequency domain [32]. In this subsection, two optimized STRCA methods are introduced. The first method is time-constraint task-related component analysis (TC-TRCA), which is designed to solve the feature selection problems in classification among multiple movement states. The second method is filter-bank task-related component analysis (FB-TRCA) [21]. The FB-TRCA optimizes the performance of STRCA in the

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**Fig. 2.** The structure of STRCA method, which consists of the spatial filter TRCA and the extracted CCP features.
binary classification between movement and rest. We first introduce the concept of TC-TRCA and FB-TRCA. Then the feature selection methods in the two methods are introduced.

1) Time-Constrained Task-Related Component Analysis: Methods in existing studies are insufficient to distinguish the differences between the grand average MRCPs of two motions. This study proposes a TC-TRCA method to solve the problem.

In previous studies on EEG signals, time windows were often used to capture the temporal characteristics of EEG signals [31], [32]. For example, in motor imagery analysis, the type of time window is a sliding time window [32]. The sliding time window can detect changes in brain activities as time flows. However, in MRCP analysis, pre-movement patterns are extracted before movement onset, and the increasing amplitude of grand average MRCP signals is located at the movement onset. Therefore, we propose a type of new start-varying time window for MRCP analysis, which is equipped with a varying start time and an end time fixed at the movement onset. Two types of time windows are given in Figure 5.

TC-TRCA uses feature selection methods to select essential features from CCP features extracted in these time windows. Figure 6 shows the flowchart of the proposed TC-TRCA. The TC-TRCA method consists of two major procedures: (1) time window analysis, and (2) feature extraction and selection.

To ensure which time window type has better performance in MRCP analysis, two window types, sliding time windows and start-varying time windows, are compared by applying the STRCA method to these two methods. By extracting CCPs with STRCA from each of these time windows, TC-TRCA can obtain all features related to the changing trend in the RP section.

2) Filter-Bank Task-Related Component Analysis: The FB-TRCA method is proposed to solve the frequency range selection problem of STRCA by incorporating the filter bank...
Fig. 5. Two types of time windows. Window type 1: sliding time window; Window type 2: start-varying time window. In both types of time windows, the window start time changes from -2 s to -1 s with a time step of 0.0625s. The length of sliding windows is 1 s. The start-varying windows end at the movement onset (0 s).

Fig. 6. The flowchart of TC-TRCA method. STRCA is used to extract CCP features from $T$ time windows. $T \times 6$ features are obtained in total. Then feature selection methods are used to select essential features from the $T \times 6$ features. The number of selected essential features are the hyper-parameters in this work. The selected essential features are then used to classify between movement state and resting state or movement state and movement state.

technique [21]. FB-TRCA shows an improved classification performance compared to STRCA. Figure 7 gives the flowchart of FB-TRCA.

FB-TRCA first divides the original EEG signals with various filter banks. Then, STRCA is used to extract CCPs from the filtered EEG signals in each of these filter banks. Finally, feature selection methods are used to select essential features from these CCPs.

3) Feature Selection Method: Because not all CCP features from filter banks or time windows matter in the classification, feature selection methods are used to select essential features from these CCP features. Feature selection will reduce the requirement for the binary classifier.

The mutual-information based approach is an important feature selection paradigm in data mining. In FB-TRCA, the effects of eight mutual-information based feature selection methods are compared [33]:

1) Mutual Information Quotient (MIQ) [24]
2) Maximum Relevance (MAXREL) [25]
3) Minimum Redundancy (MINRED) [25]
4) Minimum Redundancy Maximum Relevance (MRMR) [25]
5) Quadratic Programming Feature Selection (QPFS) [26]
6) Conditional Infomax Feature Extraction (CIFE) [27]
7) Conditional Mutual Information Minimization (CMIM) [28]
8) Maximum Relevance Minimum Total Redundancy (MRMTR) [29]

Jia’s work notes that MRMR is the feature selection method that best fits FB-TRCA [21]. Because the feature selection of TC-TRCA has not yet been discussed, the effects of these feature selection methods are compared in this work.

D. Star-Arrangement Spectral Filtering

In studies on EEG signals, movement detection is an important topic. However, multi-class pre-movement classification is still a problem that remains to be solved. This work aims to solve this problem by developing the RTRCA framework with both the FB-TRCA method and TC-TRCA method.

The RTRCA framework includes two modules. Module 1 is associated with the binary classification between movement and rest. Module 2 is associated with the classification among movements. In module 1, the EEG signals in resting state play a role as a reference and are classified against EEG signals in each of movement states. The resting state is like the center node of the star arrangement, and the movement states are like the surrounding nodes of the star arrangement. Therefore, the proposed improved method is named as star-arrangement spectral filtering (SASF). Figure 8 illustrates the flowchart of the proposed SASF. For the optimization in module 1, FB-TRCA is considered because FB-TRCA has an improved classification performance compared to STRCA. Thus, the essential features in module 1 can better measure the differences between the movement state and resting state. In module 2, the proposed TC-TRCA is used because the
TC-TRCA is designed to utilize the changing trend of grand average MRCP. Hence, the essential features can be used to distinguish two motions. To ensure that the essential features in TC-TRCA are necessary for the classification between movements, we compare the classification performance between FB-RTRCA and TC-RTRCA. The two methods are developed by replacing module 2 of RTRCA with FB-TRCA and TC-TRCA, respectively. Table III gives the module components of these methods that are developed based on the RTRCA framework.

In RTRCA, TC-RTRCA and FB-RTRCA, module 1 is STRCA. The input of module 2 is still CCP features. From the other perspective, TC-RTRCA and FB-RTRCA replace the STRCA with RTRCA in the TC-TRCA and FB-TRCA methods in Figure 6 and Figure 7. Therefore, the feature selections of module 2 in TC-TRCA and FB-TRCA are the same as those in TC-TRCA and FB-TRCA. To clearly distinguish the methods used in this work, Table IV lists the classification categories of these methods.

In SASF, feature selection with FB-TRCA changes the size of the input of module 2. It is supposed that EEG signals have been divided into $T$ time windows and $F$ filter banks. CCP features are extracted with STRCA from the $T \times F$ banks. Because the number of CCP features is $6$, $T \times F \times 6$ features are obtained. Then feature selection of FB-TRCA is used to select $K_1$ essential features from the $F \times 6$ features for each of $T$ time windows. Therefore, the input size of the module 2 of SASF is $T \times K_1$. Then, the feature selection method in TC-TRCA is used to select the $K_2$ essential features from the $T \times K_1$ features. The final $K_2$ features are used in the classification of SASF.

The SASF method can be further modified for multi-class pre-movement classification, whose flowchart is shown in Figure 9. In the multi-class version of SASF, the first modification is located at the classifier. In multi-class classification, a multi-class classifier is definitely necessary. Because multiple FB-TRCAs are used to classify the movement state and resting state, multiple CCPs in the resting state are extracted with each of these FB-TRCAs. Direct classification with a multi-class classifier between these movement states and resting state will lead to an imbalance in the sample proportion during the training process. To avoid this problem, the rest-state CCPs of the multiple FB-TRCAs are averaged; thus, the resting state and other motions have similar number of trials.

### E. Classifiers

In this work, the proposed SASF is developed based on machine-learning methods. Unlike the features extracted with deep-learning methods, feature extraction procedure does not contain other hyper-parameters except the number of selected essential features. The classifier should also be simple and with fewer hyper-parameters so that the accuracies can indicate the quality of the extracted features. Therefore, we only consider the linear discriminant analysis (LDA) classifier and the support vector machine (SVM) classifier (linear kernel) for both binary and multi-class classification.

### F. Parameter Settings

In this work, the parameters are associated with (1) the filter bank setting in FB-TRCA (2) the time window setting in TC-TRCA and (3) the selection of essential features, including the feature selection method and the selected number of features.

In the filter bank settings, the start frequency of these filter banks ranges from $1 \ Hz$ to $10 \ Hz$ with a step of $1 \ Hz$. Hence, $10$ filter banks are obtained in total. Because STRCA, RTRCA, TC-TRCA and TC-RTRCA are not involved with the selection of filter banks, the frequency range of EEG signals in these methods is set to $0.5 \sim 4 \ Hz$ by default.

In the time window setting, the window start time changes from $-2 \ s$ to $-1 \ s$ with a step of $0.0625 \ s$. The window type will be decided by the following result analysis.
Fig. 8. Binary classification with SASF. SASF is an extension of the RTRCA that incorporates FB-TRCA and TC-TRCA. In module 1, STRCA is replaced with FB-TRCA to classify between movement and rest. In module 2, TC-TRCA is introduced to optimize the features from module 1. The essential features selected in TC-TRCA are used to classify between two motions. The input of SASF includes a resting state and two movement states. The resting state is connected to each of the movement states by the classification in module 1. In the star arrangement, the resting state is the center node and the movement states are the surrounding nodes. The arrangement of the input is like a star.

| Movement vs Resting | Movement vs Movement | Description |
|---------------------|---------------------|-------------|
| STRCA               | RTRCA               | Basic binary classification method |
| TC-TRCA             | TC-RTRCA            | Optimized with time window selection |
| FB-TRCA             | FB-RTRCA            | Optimized with filter bank selection |
| -                   | SASF                | Optimized with both filter bank and time window selection |

Fig. 9. Multi-class classification with SASF. The binary SASF can be easily extended to multi-class version. In module 1, more FB-TRCAs are introduced to classify between the increased motions and the rest. In module 2, the mutual-information based feature selection method in TC-TRCA is also suitable for multi-class selection. After extracting essential features with feature selection methods, a multi-class classifier is applied to the classification of multiple motions. The CCP features in resting state extracted in module 1 are averaged across the various FB-TRCAs to avoid the imbalance of sample proportion problem. Then the CCP features of resting state can also be used as the input of module 2.
The number of essential features is the only hyper-parameter in this work. According to Jia’s work, the FB-TRCA is equipped with the MRMR feature selection method [21]. Because FB-TRCA achieves better performance with more than 13 features, the number of essential features is set to 15 when applying FB-TRCA in module 1 of SASF. The feature selection method in TC-TRCA needs to be determined in the following experiment, which is the parameter searching process. When evaluating these methods that need parameter searching, the number of selected features where the accuracies change very slightly is adopted.

III. RESULT

In this work, we propose the TC-TRCA method and the SASF method. To evaluate the TC-TRCA method, it is necessary to (1) choose the type of time windows, (2) decide the feature selection method and (3) decide the number of selected essential features. To evaluate the SASF method, it is necessary to decide between TC-TRCA and FB-TRCA as the module 2 of the RTRCA framework. Therefore, the results are analysed from three perspectives: (1) Binary classification: movement and rest; (2) Binary classification: movement and movement; (3) Multi-class classification.

A. Binary Classification: Movement and Rest

Although TC-TRCA is designed to solve the feature selection problem in classification between movement and movement, TC-TRCA can also be used in the classification between movement and rest. In this subsection, the classification performance of TC-TRCA is compared with STRCA and FB-TRCA. When evaluating the classification performance of each method, the accuracies are averaged across 15 subjects and 10 folds and 6 motions.

1) Decision on Window Type: In TC-TRCA, we propose a new type of time window, the start-varying time window (type 2). The performance of the start-varying window is compared with the other commonly used time window, the sliding time window (type 1). Because this comparison aims to decide the time window type in which the CCPs have better performance, the LDA classifier is used as the binary classifier.

In Figure 10, two window types are compared as the window start time changes from -2 s to -1 s with a step of 0.0625 s. From the results shown in Figure 10, the proposed start-varying time window has better classification performance than the sliding time window. At the beginning of the RP section (-2 s), the accuracy of the sliding window is extremely worse than that of the start-varying window. When the window start time is -2 s, the start-varying time window covers -2 to 0 s, and the sliding time window covers -2 to -1 s. The sliding time window cannot cover the time points around movement onset, where the amplitude of the grand average MRCP increases.

Therefore, the window type used in TC-TRCA is the proposed start-varying time window. Because the start time of the start-varying window is not limited to the length of the time windows, the window start time changes from -2 s to 0 s with a step of 0.0625 s in TC-TRCA.

2) Decision on Feature Selection Method: In TC-TRCA, feature selection methods are used to select the essential features from CCP features of all time windows. Figure 11 gives the classification accuracies of these feature selection methods as the number of selected features increases. The selected essential features are classified with LDA or SVM classifiers. In Figure 11, the accuracies of most of the feature selection methods become steady when the number of selected features increases. In Table V, the accuracies of TC-TRCA with an acceptable number of selected features are compared to the other two methods, STRCA and FB-TRCA. Although TC-TRCA can improve the classification accuracy of STRCA, FB-TRCA is better than TC-TRCA in the binary classification between movement and rest.

B. Binary Classification: Movement and Movement

Binary classification between movement and movement is a challenging work in brain-computer interface systems. This work proposes the RTRCA method and considers the RTRCA method as a framework. Then, we develop the RTRCA framework with feature selections on time windows and filter banks. STRCA and RTRCA have the same output, including two CCPs. By applying feature selection on time windows or filter banks to the output of STRCA, TC-TRCA and FB-TRCA are developed, as shown in Figure 5 and Figure 7. With the same operation, TC-RTRCA and FB-RTRCA are developed by applying feature selections on time windows and filter banks to the output of RTRCA, respectively. Therefore, TC-TRCA and FB-TRCA measure the effects of feature selection on the classification between movement state and resting state; TC-RTRCA and FB-RTRCA measure the effects of feature selection on the classification between two movement states. In Table VI, the classification accuracies of RTRCA, TC-RTRCA and FB-RTRCA are compared. When evaluating the classification performance of these methods, the accuracies are averaged across 15 subjects, 10 folds and 15 motion pairs. Unlike the case of classification between movement and rest, TC-RTRCA shows a better performance than FB-RTRCA.

By concluding the comparison results in Table V and Table VI, it can be seen that TC-TRCA is better than FB-TRCA in...
Fig. 11. Parameter searching on the number of essential features in TC-TRCA. The accuracies become steady as the number of selected essential features increase for both the LDA and SVM classifiers.

TABLE V

| Method  | STRCA | STRCA | TC-TRCA | TC-TRCA | FB-TRCA | FB-TRCA |
|---------|-------|-------|---------|---------|---------|---------|
| Classifier | LDA   | SVM   | LDA     | SVM     | LDA     | SVM     |
| Selection | -     | -     | MRMTR   | MRMTR   | MRMTR   | MRMTR   |
| Accuracy  | 0.8273±0.1149 | 0.8391±0.1106 | 0.8280±0.1110 | 0.8358±0.1123 | 0.8336±0.1075 | 0.8552±0.1039 |

TABLE VI

| Method  | RTRCA | RTRCA | TC-RTRCA | TC-RTRCA | FB-RTRCA | FB-RTRCA |
|---------|-------|-------|---------|---------|---------|---------|
| Classifier | LDA   | SVM   | LDA     | SVM     | LDA     | SVM     |
| Selection | -     | -     | MRMTR   | MRMTR   | MRMTR   | MRMTR   |
| Accuracy  | 0.5519±0.1402 | 0.5494±0.1016 | 0.6218±0.1450 | 0.6374±0.1424 | 0.6254±0.1383 | 0.6225±0.1328 |

the classification of two movement states but is worse than FB-TRCA in the classification between movement and rest. In the RTRCA framework, module 1 extracts CCP features with classification between the movement and rest; module 2 extracts features to distinguish different motions. Therefore, the ideal RTRCA-based method is developed by incorporating FB-TRCA into module 1 and incorporating TC-TRCA into module 2.

Figure 12 illustrates the parameter searching process on the number of features in the module 2 of the ideal RTRCA-based method, SASF. SASF shows the best performance when the feature selection method of module 2 is MRMTR and the classifier is an LDA. Figure 13 gives the comparison of the SASF method against other movement-vs-movement methods, including the benchmark DCNN. The proposed SASF method greatly improves the classification performance and makes the classification between two motions reliable.

C. Multi-Class Classification

In previous studies, there is no such method that can be used in the classification of multiple motions. The proposed SASF method can easily realize this purpose.

We first apply the SASF method to classify the 6 motions in the dataset used. When evaluating the classification performance of each method, the accuracies are averaged across 15 subjects and 10 folds. The parameter search process of module 2 is shown in Figure 14. The feature selection method MRMTR shows better performance than the others. The classification accuracies achieve state of the art performance, which means that the motions can be reliably detected with the proposed SASF method.

In the classification of 7 motions (6 motions plus the resting state), the features of resting state cannot be extracted as the other 6 motions and some modifications are taken. In module 1 of SASF, we take the mean of the CCPs of resting state across six FB-TRCAs. In module 2 of SASF, two cases are considered during the training of feature selection:

1) The feature index trained with CCPs of 6 motions is directly used to select the features from the averaged CCPs of resting states;

2) The feature index is trained with CCPs of 6 motions and the averaged CCPs of resting states.

Each of the two cases can realize feature selection for the resting state. In Figure 15, the confusion matrices of classification with 6 motions and the two cases of classification with 7 motions are given. These confusion matrices are generated by adding up the confusion matrices of 15 subjects and 10 folds, which are classified with the LDA classifier.

In Figure 15, the correct ratio of 6 motions is 0.9549, and the ratios of two cases of 7 motions are 0.9474 and 0.9493.
Fig. 12. Parameter searching on the number of essential features in the module 2 of binary SASF. Although accuracies of both LDA and SVM classifier become steady as the number of selected features increases, LDA classifier has a better performance than SVM classifier.

Fig. 13. Binary classification accuracy comparison between movement and movement. The two RTRCA-based methods (FB-RTRCA and TC-RTRCA), have an improved performance compared to the previous DCNN method. The proposed SASF method greatly improves the classification accuracy between movement and movement.

From the comparison between the two cases of 7 motions, it can be seen that applying the feature index trained with movements to the feature selection of the resting state does not have significant influence on the final classification results.

Uniform Manifold Approximation and Projection (UMAP) is a dimension reduction algorithm that is able to visualize high-dimensional data in a two-dimensional view [34]. In Figure 16, the UMAPs of features in multi-class classification are given, which includes both the training set and testing set of Subject 1. In the UMAP of the training set, the features of these motions are clearly separated. In addition, the feature distributions are similar in the training set and testing set.

IV. DISCUSSION

This work proposes the SASF method to solve the multi-class pre-movement classification problem by incorporating the FB-TRCA and TC-TRCA into the RTRCA framework. The classification between movement and movement with MRCP signals is actually about finding the differences between the grand average CPRM signals of these movements. In STRCA, the CCP features are used to measure the similarity by the coefficients between the unlabeled trials and the grand average MRCPs of both movement and rest. Therefore, we develop the SASF method based on STRCA. The SASF method consists of three keys, RTRCA, TC-TRCA and FB-TRCA. How the SASF method works can be explained in three aspects from the perspective of grand average MRCP.

A. RTRCA

STRCA and RTRCA have the same processing procedure. The difference between the two methods is that STRCA measures the difference between the movement state and resting state but RTRCA measures the difference between two motions. STRCA calculates the correlation coefficient between the movement state and the resting state. RTRCA is combined with the two STRCAs. Each of the STRCAs is used to distinguish one of the two motions from the rest. Afterwards RTRCA classifies the two motions with the CCPs from two STRCAs.

The grand average MRCP of movement has an increasing trend, while the grand average MRCP of the resting state is a kind of relatively steady signal. Because the grand average
Fig. 14. Parameter searching on the number of essential features in the module 2 of multi-class SASF. When equipped with the MRMTR and the LDA classifier in module 2, SASF achieves the most stable and outstanding classification performance.

Fig. 15. Confusion matrices of classification accuracies of multi-class SASF. (a) 6 motions classification; (b) 7 motions classification-case 1: the feature index of module 2 trained in (a) is directly applied to the resting state; (c) 7 motions classification-case 2: the feature index of module 2 is recalculated with 6 motions and the resting state. The correct ratios of (a), (b) and (c) are 0.9549, 0.9474 and 0.9493, respectively.

Fig. 16. UMAP: Feature distributions of the training set and testing set of Subject 1. In the used UMAP setting, the neighbor number is 10. The minimum spacing of points in the output embedding is set to 0.001, and the embedding optimization iteration number is 200. The two-dimensional embedding of the data is normalized with minimal-maximal normalization before visualization.
MRCPs of the two motions have both an increasing trend, the differences between grand average MRCPs are difficult to be determined directly. However, the grand average MRCPs of the movement state and resting state have clear differences because their trends have major differences. If we denote the grand average MRCPs of two motions and resting state as $d_1$, $d_2$, and $d_0$, the STRCA measures the differences between two motions and the resting state with $d_1 = d_1 - d_0$ and $d_2 = d_2 - d_0$. When classifying two motions directly with STRCA, the difference between two motions is denoted as $\Delta d = d_2 - d_1$. The difference $\Delta d$ is difficult to measure because the grand average MRCPs of the two motions are close to each other. By introducing the resting state as a reference, the RTRCA framework transforms the measurement on $\Delta d$ to the measurement on $[d_1, d_2]$. Telling the differences of two motions by discriminating two values $d_1$ and $d_2$ is much easier than that by discriminating only value $\Delta d$.

The other possible advantage of introducing the resting state as a reference in the RTRCA framework is associated with the start-varying time windows in module 2. Due to the noise present in EEG signals, the correlation coefficient between two signals changes as the length of the time window varies, although a part of the signals is always covered in the start-varying time windows. When using TC-TRCA to measure the correlations, the coefficients will inevitably be influenced by the start-varying time windows. If TC-TRCA is directly used in the classification of two motions, the difference $\Delta d$ contains the influences. The influences cannot be compensated for during the classification. With the RTRCA framework, although $d_1$ and $d_2$ are both influenced by the start-varying time window, the influences can be compensated for because both $d_1$ and $d_2$ are used in the classification of two motions.

B. TC-TRCA

In this work, TC-TRCA is proposed to optimize the feature selection in the grand average MRCP. Previous studies have tried to find the differences between movement state and resting state from grand average MRCP. The selected features from grand average MRCP can be understood in three aspects.

1. Overall constant: The SSSF method adopts the mean of signals as the features. In the RP section, because the amplitude increases when the time point approaches the movement onset, the mean of the signals will also increase. Therefore, SSSF can capture the slight differences between movement and rest.

2. Overall similarity: The STRCA method uses the correlation coefficients to measure the similarity between the unlabeled trials and the grand average MRCPs of both movement and resting states. In comparison to the features in SSSF, the CCP features in STRCA can observe more differences between movement and rest.

3. Overall trend: This work proposes the TC-TRCA method, which incorporates start-varying time windows into the STRCA method. Hence, the TC-TRCA can measure the similarity of signals as the window start time changes; and then seize the changing trend of grand average MRCP.

C. FB-TRCA

In comparison to STRCA and TC-TRCA, features extracted with FB-TRCA can achieve better classification performance in the classification between movement state and resting state (Table V).

In module 1 of the RTRCA framework, STRCA is first used to determine the differences between movement and rest. In other words, the module 1 of RTRCA aims to find the differences between movement and rest. Hence, module 2 of RTRCA can focus on searching the differences among movements. Replacing STRCA with FB-TRCA in module 1 can provide module 2 with more discriminant features. However, which of FB-TRCA and TC-TRCA is better for the feature selection in module 2 is unknown, so the accuracies of FB-RTRCA and TC-RTRCA are compared in Table VI. The results in table VI show that TC-RTRCA performs better than FB-RTRCA. Therefore, TC-TRCA is used in module 2 of the proposed SASF method.

In Figure 15, the two cases of 7 motions have close correct ratios of 0.9474 and 0.9493. This means that the feature distributions of the movement state and resting state in module 1 have been separated entirely with FB-TRCA so that the feature selection in module 2 is less influenced by the feature distribution of the resting state. FB-TRCA plays an important role in this step.

By incorporating TC-TRCA and FB-TRCA into the RTRCA framework, the proposed SASF achieves state of the art performance for both binary and multi-class pre-movement classification. However, because the proposed SASF method is derived from the STRCA method, which is an offline analysis, SASF is currently used in offline cases. The online SASF is the future work in our research plan.

V. CONCLUSION

Multi-class pre-movement decoding is a challenge in EEG signal processing. As far as the authors know, there is no such research that can solve the multi-class pre-movement classification problem. To solve this problem, this work first proposes the RTRCA framework. Then, we propose the TC-TRCA method to extract features that can be used in the multi-class pre-movement classification. By incorporating the FB-TRCA and the proposed TC-TRCA into the RTRCA framework, we develop and propose the SASF method. The proposed SASF method successfully classifies multiple motions and achieves state of the art classification performance. This work is expected to help detect movement intention in disabled patients or patients with paralysis whose limb movements cannot be measured. In addition, this work paves the way for understanding the relationship between the human brain and limb movements.
REFERENCES

[1] Gerwin Schalk, Dennis J McFarland, Thilo Hinterberger, Niels Birbaumer, and Jonathan R Wolpaw. BC12000: A General-Purpose Brain-Computer Interface (BCI) System. IEEE Transactions on biomedical engineering, 51(6):1034–1043, 2004.

[2] Rabie Ramadan and Athanasios Vlaskos. Brain Computer Interface: Control Signals Review. Neurocomputing, 223:26–44, 2016.

[3] Hyun-Seok Kim, Min-Hee Ahn, and Byoung-Kyong Min. Deep-Learning-Based Automatic Selection of Fewest Channels for Brain-Machine Interfaces. IEEE Transactions on Cybernetics, pages 1–13, 2021.

[4] Natasha Padfield, Jaime Zabalza, Haimin Zhao, Valentin Masero, and Jinghe Rem. EEG-Based Brain-Computer Interfaces Using Motor Imagery: Techniques and Challenges. Sensors, 19(6):1423, 2019.

[5] Sharon Olsen, Nada Signal, Imran Khan Niazi, Thomas Christensen, Mads Jochumsen, and Denise Taylor. Paired Associative Stimulation Delivered by Pairing Movement-Related Cortical Potentials With Peripheral Electrical Stimulation: An Investigation of the Duration of Neuromodulatory Effects. Neuro modulation: Technology at the Neural Interface, 21(4):362–367, 2018.

[6] No-Sang Kwak and Seong-Whan Lee. Error Correction Regression Framework for Enhancing the Decoding Accuracies of EEG Brain–Computer Interfaces. IEEE Transactions on Cybernetics, 50(8):3654–3667, 2020.

[7] Daniela Iacoviello, Andrea Petracca, Matteo Spezialetti, and Giuseppe Farina. Detection of Movement Related Cortical Potentials. IEEE Transactions on rehabilitation engineering, 28(3):687–698, 2020.

[8] Patrick Ofner, Andreas Schwarz, Joana Pereira, and Gernot R. Müller-Putz. Upper Limb Movements can be Decoded from the Time-Domain of Low-Frequency EEG. PLOS ONE, 12(8):e0182578, 2017.

[9] Ji-Hoon Jeong, No-Sang Kwak, Cuntai Guan, and Seong-Whan Lee. Decoding Movement-Related Cortical Potentials Based on Subject-Dependent and Section-Wise Spectral Filtering. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28(3):687–698, 2020.

[10] Feng Duan, Hao Jia, Zhe Sun, Kai Zhang, Yangyang Dai, and Yu Zhang. Decoding Premovement Patterns with Task-Related Component Analysis. Cognitive Computation, 2021.

[11] Hao Jia, Zhe Sun, Feng Duan, Yu Zhang, Cesar F. Ciaiafa, and Jordi Solé-Casals. Improving Premovement Patterns Detection with Filter Bank Selection. Under Revision.

[12] Nadia Mammone, Cosimo Ieracitano, and Francesco C. Morabito. A Deep CNN Approach to Decode Motor Preparation of Upper Limbs from Time–Frequency Maps of EEG Signals at Source Level. Neural Networks, 124:357–372, 2020.

[13] Patrick Ofner, Andreas Schwarz, Joana Pereira, Daniela Wyss, Renate Wildburger, and Gernot R. Müller-Putz. Attempted Arm and Hand Movements can be Decoded from Low-Frequency EEG from Persons with Spinal Cord Injury. Scientific Reports, 9(1):7134, 2019.

[14] Chris Ding and Hanchuan Peng. Minimum Redundancy Feature Selection from Microarray Gene Expression Data. In Computational Systems Bioinformatics, CSB2003. Proceedings of the 2003 IEEE Bioinformatics Conference. CSB2003, pages 523–528, 2003.

[15] Hanchuan Peng, Fuhui Long, and Chris Ding. Feature Selection Based on Mutual Information Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy. IEEE Transactions on Pattern Analysis and Machine Intelligence, 27(8):1226–1238, 2005.

[16] Irene Rodríguez-Lujan, Ramon Huerta, Charles Elkan, and Carlos Santa Cruz. Quadratic Programming Feature Selection. J. Mach. Learn. Res., 11:1491–1516, 2010.

[17] Dalin Zhang, Lina Yao, Kaixuan Chen, Sen Wang, Xiaojun Chang, and Junhao Liu. Making Sense of Spatio-Temporal Preserving Representations for EEG-Based Human Intention Recognition. IEEE Transactions on Biomedical Engineering, 50(7):3033–3044, 2020.

[18] Xuan Vinh Nguyen. Information theoretic feature selection analysis. J. Mach. Learn. Res., 15(1):016033, 2020.

[19] Kun Wang, Minpeng Xu, Yijun Wang, Shanshan Zhang, Long Chen, and Dong Ming. Enhance Decoding of Pre-movement EEG Patterns for Brain–Computer Interfaces. Journal of Neural Engineering, 17(1):016033, 2020.

[20] Patrick Ofner, Andreas Schwarz, Joana Pereira, and Gernot R. Müller-Putz. Upper Limb Movements can be Decoded from the Time-Domain of Low-Frequency EEG. PLOS ONE, 12(8):e0182578, 2017.

[21] Ji-Hoon Jeong, No-Sang Kwak, Cuntai Guan, and Seong-Whan Lee. Decoding Movement-Related Cortical Potentials Based on Subject-Dependent and Section-Wise Spectral Filtering. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28(3):687–698, 2020.

[22] Peng Duan, Hao Jia, Zhe Sun, Kai Zhang, Yangyang Dai, and Yu Zhang. Decoding Premovement Patterns with Task-Related Component Analysis. Cognitive Computation, 2021.

[23] Hao Jia, Zhe Sun, Feng Duan, Yu Zhang, Cesar F. Ciaiafa, and Jordi Solé-Casals. Improving Premovement Patterns Detection with Filter Bank Selection. Under Revision.

[24] Nadia Mammone, Cosimo Ieracitano, and Francesco C. Morabito. A Deep CNN Approach to Decode Motor Preparation of Upper Limbs from Time–Frequency Maps of EEG Signals at Source Level. Neural Networks, 124:357–372, 2020.

[25] Patrick Ofner, Andreas Schwarz, Joana Pereira, Daniela Wyss, Renate Wildburger, and Gernot R. Müller-Putz. Attempted Arm and Hand Movements can be Decoded from Low-Frequency EEG from Persons with Spinal Cord Injury. Scientific Reports, 9(1):7134, 2019.

[26] Chris Ding and Hanchuan Peng. Minimum Redundancy Feature Selection from Microarray Gene Expression Data. In Computational Systems Bioinformatics, CSB2003. Proceedings of the 2003 IEEE Bioinformatics Conference. CSB2003, pages 523–528, 2003.

[27] Hanchuan Peng, Fuhui Long, and Chris Ding. Feature Selection Based on Mutual Information Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy. IEEE Transactions on Pattern Analysis and Machine Intelligence, 27(8):1226–1238, 2005.

[28] Irene Rodríguez-Lujan, Ramon Huerta, Charles Elkan, and Carlos Santa Cruz. Quadratic Programming Feature Selection. J. Mach. Learn. Res., 11:1491–1516, 2010.

[29] Dalin Zhang, Lina Yao, Kaixuan Chen, Sen Wang, Xiaojun Chang, and Junhao Liu. Making Sense of Spatio-Temporal Preserving Representations for EEG-Based Human Intention Recognition. IEEE Transactions on Biomedical Engineering, 50(7):3033–3044, 2020.

[30] Xuan Vinh Nguyen. Jeffrey Chan, Simone Romano, and James Bailey. Effective Global Approaches for Mutual Information Based Feature Selection. In Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, page 512–521. Association for Computing Machinery, 2014.

[31] Masaki Nakanishi, Yijun Wang, Xiaogang Chen, Yute Wang, Xiaorong Gao, and Ziyeping Jia. Enhancing Detection of SSVEPs for a High-Speed Brain Speller Using Task-Related Component Analysis. IEEE Transactions on Biomedical Engineering, 66(1):104–112, 2018.

[32] Yu Zhang, Chang S. Nam, Guoxu Zhou, Jing Jin, Xingyu Wang, and Andrej Cichocki. Temporally Constrained Sparse Group Spatial Patterns for Motor Imagery BCI. IEEE Transactions on Biomedical Engineering, 50(7):3033–3044, 2020.

[33] Xuan Vinh Nguyen. Jeffrey Chan, Simone Romano, and James Bailey. Effective Global Approaches for Mutual Information Based Feature Selection. In Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, page 512–521. Association for Computing Machinery, 2014.

[34] Masaki Nakanishi, Yijun Wang, Xiaogang Chen, Yute Wang, Xiaorong Gao, and Ziyeping Jia. Enhancing Detection of SSVEPs for a High-Speed Brain Speller Using Task-Related Component Analysis. IEEE Transactions on Biomedical Engineering, 66(1):104–112, 2018.