

Subject and Class Specific Frequency Bands Selection for Multiclass Motor Imagery Classification

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ABSTRACT: EEG-based discrimination among motor imagery states has been widely studied for brain-computer interfaces (BCIs) due to the great potential for real-life applications. However, in terms of designing a motor imagery-based BCI system, a lot of research in the literature either uses a frequency band of interest selected manually based on the visual analysis of EEG data or is set to a general broad band, causing performance degradation in classification. In this article, we propose a novel method of selecting subject and class specific frequency bands based on the analysis of a channel-frequency matrix, which we call a channel-frequency map. We operate the classification process for each frequency band individually, i.e., spatial filtering, feature extraction, and classification, and determine a class label for an input EEG by considering the outputs from multiple classifiers together at the end. From our experiments on a public dataset of BCI Competition IV (2008) II-a that includes four motor imagery tasks from nine subjects, the proposed algorithm outperformed the common spatial pattern (CSP) algorithm in a broad band and a filter bank CSP algorithm on average in terms of cross-validation and session-to-session transfer rate. Furthermore, a considerable increase of classification accuracy has been achieved for certain subjects. We also would like to note that the proposed data-driven frequency bands selection method is applicable to other kinds of single-trial EEG classifications that are based on modulations of brain rhythms, by no means limited to motor imagery-based BCI applications.

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I. INTRODUCTION

Brain-computer interfaces (BCIs) establish a direct communication pathway between human intentions and external electronic devices via the translation of electrical brain signals into user commands

without using muscle activity or peripheral nerves. Because of their great potential in medical and industrial applications, they have been considered an emerging technology and have been of great interest to many research groups (Pfurtscheller and Neuper, 2001; Vaughan et al., 2006; Birbaumer and Cohen, 2007; Lotte et al., 2007; Hoffmann et al., 2008; Nijholt and Tan, 2008; van Gerven et al., 2009; Cecotti, 2010; Martens and Leiva, 2010). From a medical point of view, because they are not dependent on neuromuscular control, BCIs are expected to be able to provide severely disabled people suffering from the disastrous neuromuscular disorders (e.g., amyotrophic lateral sclerosis, brainstem stroke, or spinal cord injuries) with an efficient channel of communication to the outside world.

However, the high complexity of the human brain and low signal-to-noise ratio (SNR) of EEG signals prevents the BCI systems from decoding every human mental state or intent. A small subset of states such as mental arithmetic, visual attention, and motor imagery have been efficiently and robustly used for word spellers (Krusienski et al., 2008; Rakotomamonjy and Guigue, 2008; Salvaris and Sepulveda, 2009; Cecotti, 2010; Martens and Leiva, 2010), games (Tangermann et al., 2008), and robot or wheelchair control (Philips et al., 2007; Galan et al., 2008). Increasing attention has been devoted to the analysis of EEG signals evoked by motor imagery because those signals can be elicited both asynchronously and continuously. There are also well-known neuro-physiological phenomena that the signal power in the motor and somatosensory cortex is suppressed or augmented due to the loss of synchrony in a particular frequency range during motor imagery, which are called event-related desynchronization (ERD) or event-related synchronization (ERS), respectively (Pfurtscheller and Neuper, 2001).

Brain rhythms related to the imagination of movement are known to be broadly concentrated in the μ (12–16 Hz) and β (18–24 Hz) frequency bands. However, the frequency bands are highly variable over different motor imageries and between subjects. In terms of designing a motor imagery-based BCI system, the selection of proper frequency bands in which we filter the EEG data before extracting features are one of the most challenging problems in BCIs. In general, a frequency range of importance in

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discrimination of EEG signals is identified by the visual analysis on the data transformed into a frequency domain requiring a time-consuming process for each set of mental tasks to be classified and for each subject.

To our knowledge, the frequency bands on which the process in a BCI system operates are either selected manually or set to a general broad band. Only a few papers in the literature (Dalponte et al., 2007; Chin et al., 2009; Fazli et al., 2009) have partially addressed the selection of frequency bands. In this article, we propose a novel method of selecting subject and class specific frequency bands in motor imagery classification based on time-frequency map analysis using event-related spectral perturbation (ERSP) (Makeig et al., 2004). In each of the selected frequency bands, the classification process operates individually and a class label for an input EEG is determined by considering the outputs from multiple classifiers together at the end. An overview of the proposed motor imagery classification system is illustrated in Figure 1, where the thick solid arrows denote multiple streams operated in parallel. We implement a one-versus-the-rest strategy in finding optimal spatial filters and training support vector machines (SVMs).

This article is structured as follows. Section II introduces related work, whereas Section III describes the experimental setup of the classified EEG dataset and preprocessing methods. In Section IV, we propose a method of frequency band selection and elucidate our approach to extracting features and designing classifiers. Experimental results are then presented in Section V and a concluding discussion follows in Section VI.

II. RELATED WORK

A noninvasive EEG-based BCI suffers from low SNR and low spatial resolution from volume conduction effects, and a curse of dimensionality problem from multiple electrodes. Furthermore, it is known that the electrical signals of human brain activity are highly variable inter-subjects and inter-trials even for the same subjects, yielding subpar performance in the classification of electrical brain activity, which makes their application still far from viable for the real life.

Recently, techniques based on machine learning (ML) have been considered to be a useful tool to circumvent these problems. When compared with conventional approaches of univariate data analysis, ML allows coping with multiple random variables simultaneously. One of the most widely used methods in BCIs is the common spatial pattern (CSP) (Koles, 1991), thanks to its simplicity in interpretation and implementation. The CSP algorithm finds spatial filters that transform raw EEG patterns of two classes to be maximally discriminative based on the ratio of the variance of the data conditioned for one class to the variance of the data conditioned for the other class. In the case of left-hand and right-hand motor imagery classification, spatial filters can be designed to extract class-conditional components that maximally differentiate EEG data of left-hand motor imagery from those of right-hand motor imagery, or vice versa. Because of the binary nature and vulnerability to outliers, many research groups have devoted their efforts to extend the conventional CSP and proposed variants of CSP (Lemm et al., 2005; Dornhege et al., 2006; Ang et al., 2008; Blankertz et al., 2008; Grosse-Wentrup and Buss, 2008; Wang and Zheng, 2008; Chin et al., 2009; Haiping et al., 2010). Gouy-Pailler et al. (2010) extended the method of joint approximate diagonalization (JAD), which earlier proved to be useful to find efficient spatial filters in the context of multiclass motor imagery BCIs in (Grosse-

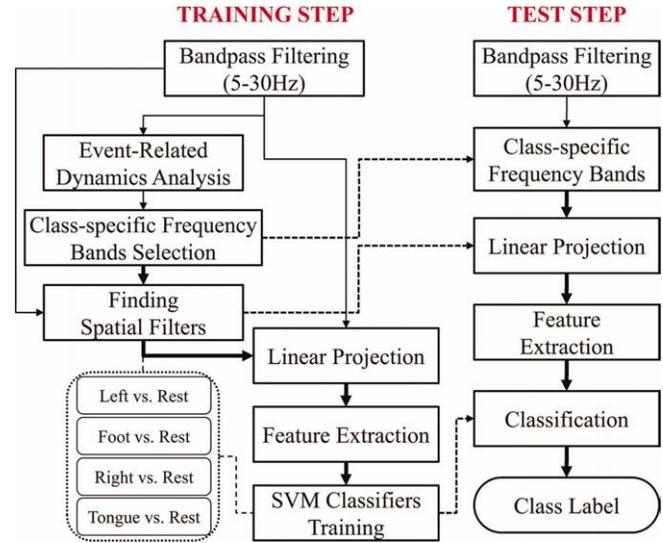


Figure 1. Overview of the proposed method. The thick solid lines represent multiple streams, one for each frequency band, running in parallel, and the dotted lines represent an exchange of information. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Wentrup and Buss, 2008), to recover task-related nonstationary brain sources using a maximum likelihood framework.

Although a wideband of 8–30 Hz covers responsive frequency components activated during motor imagery, Ramoser et al. (2000) demonstrated that the most responsive frequency bands varies over subjects. Fazli et al. (2009) focused on decoding EEG data for subject-independent BCI by constructing a library of subject-specific spatio-temporal filters from a large database of EEG recordings of 83 BCI users and deriving a subject independent classifier. Dalponte et al. (2007) proposed a method for the selection of time and frequency intervals for effective feature extraction in EEG signals for BCI applications by searching a huge space of quantized frequency and time intervals.

To address the problem of selecting the subject-specific frequency bands for the CSP algorithm, Ang et al. (2008) proposed to dissect a broad frequency range of interests into small nonoverlapping filter banks and applied a CSP algorithm to each band, which they called the filter bank common spatial pattern (FBCSP). Later, Chin et al. (2009) extended it for multiclass motor imagery classification. However, when an informative frequency band ranges over two or more consecutive bands, the FBCSP method of using the predefined and nonoverlapping bandwidth in a consecutive frequency band enforces to divide the effective bands into multiple bands and process them independently. This can cause poor performance in classification and make it difficult to analyze the results.

In this article, we propose a novel method of data-driven frequency band selection for multiclass motor imagery classification. Unlike Chin et al.'s (2009) method (Rakotomamonjy and Guigue, 2008), in our method, we consider only the frequency components that are highly responsive to each motor imagery and on top of those components we build frequency bands, each of which is composed of the consecutive frequency components having different bandwidth and sizes, and perform the ensuing processes individually.

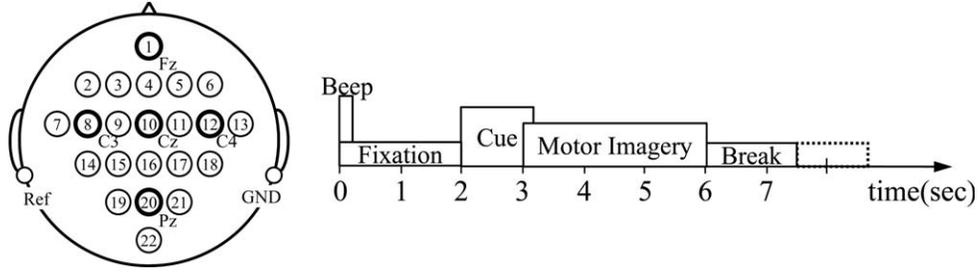


Figure 2. Experimental setup. Montage of the 22 electrodes (left) and timing scheme of the paradigm (right) (Brunner et al., 2008).

III. EXPERIMENTAL SETUP AND PREPROCESSING

We investigate a dataset of the publicly available web-based BCI competition to present the effectiveness of the proposed method. Later, we compare the results of the proposed method with those of the competition winners and other methods published in the literature.

A. Experimental Setup and Mental Tasks. We use the dataset IIa of BCI Competition IV (2008) (<http://www.bbc.de/competition/iv/#datasets>) provided by the BCI research group at Graz University (Brunner et al., 2008), which contains EEG signals recorded from nine subjects performing four different motor imagery tasks, i.e., left-hand, right-hand, foot, and tongue, comprised of two sessions conducted on different days. Each session includes six runs separated by short breaks, and a run is further composed of 48 trials; there are 12 trials per motor imagery task and 288 trials in total per session.

The EEG data was acquired using 22 AG/AgCl electrodes whose montage is presented in Figure 2(left). The signals were sampled at 250 Hz and bandpass-filtered between 0.5 Hz and 100 Hz. An additional 50 Hz notch filter was also applied to suppress line noise. The timing scheme of the experimental paradigm is depicted in Figure 2(right). The subjects were asked to carry out the motor imagery task corresponding to the cue in the form of an arrow pointing either to the left (left hand, class 1), right (right hand, class 2), down (foot, class 3), or up (tongue, class 4). Refer Brunner et al., 2008 for the detailed explanation.

B. Data Preprocessing. The EEG signals were bandpass-filtered between 5 Hz and 30 Hz covering μ (8–13 Hz) and β (14–30 Hz) rhythms that are known as related to motor imageries. We then applied small Laplacian derivation calculated by subtracting four surrounding channels with weights equal to the central one, to remove artifacts and noise. In this article, as we are interested in the selection of the frequency bands related to motor imagery classes, we considered all channels. Samples in between 0 s and 1 s before the cue-onset and those in between 0.5 s and 2.5 s after the onset of the stimulus, respectively, were used for baseline and feature extraction for both training and evaluation. The first 0.5 s period after the cue-onset is excluded as it contains the spontaneous responses to the visual stimulus.

IV. PROPOSED METHOD

A. Event-Related Brain Dynamics Analysis. In this article, we use an ERSP, a generalization of the ERD/ERS, to measure the event-related brain dynamics for the analysis of time-locked EEG spectrum induced by motor imagery. An ERSP measures dynamic changes of EEG signals evoked by an experimental stimulus such as motor imagery as a function of time in the broadband frequency spec-

trum (Makeig, 1993). The spectral changes involved in motor imageries are more than one frequency or frequency bands depending on the subjects and the stimuli. This motivates us to analyze a full-spectrum ERSP and find informative frequency bands on brain dynamics rather than considering the predefined and fixed narrow-band ERD/ERS.

Here, we briefly introduce a method to compute an ERSP related to an experimental event from a chunk of EEG data corresponding to that event. The spectra of the baseline EEG immediately preceding each stimulus is first calculated. Next, we divide the EEG signals of the k th trial into segments with a fixed-length overlapping sliding window. Sample points of each segment in a window of the c th channel are transformed into a frequency domain, here we use a complex morlet wavelet, yielding spectra $S_{i,k}^c(f, t)$ where f and t denote the frequency and time index, respectively, and i is a class label. Then, we normalize the power spectra by dividing their respective mean baseline power spectra as follows:

$$\hat{S}_{i,k}^c(f, t) = \frac{|S_{i,k}^c(f, t)|^2}{|B_{i,k}^c(f)|^2} \quad (1)$$

where $|S_{i,k}^c(f, t)|^2$ represents power spectra of the c th channel at the frequency f and the time point t during i class motor imagery, and $|B_{i,k}^c(f)|^2$ is the mean power spectra of the baseline summed over time points. We finally compute the average of the normalized response transforms for the K trials in each class producing an average ERSP in a time-frequency domain.

$$\text{ERSP}_i^c(f, t) = \frac{1}{K} \sum_{k=1}^K \hat{S}_{i,k}^c(f, t) \quad (2)$$

B. Channel-Frequency Map. The ERSP measures the brain dynamics of each channel independently. However, due to the nature of EEG measurement, neighboring electrodes may have common sources and spectral attributes that contribute to measured EEG signals. We combine the multichannel distributed ERSPs into a matrix by concatenating the time-domain averaged out ERSP of each channel as follows

$$\text{CFM}_i(C, F) = [X_i^1, \dots, X_i^c, \dots, X_i^C] \quad (3)$$

$$X_i^c = \frac{1}{T} \sum_{t=1}^T \text{ERSP}_i^c(f, t) \quad (4)$$

where C and F denote the number of channels and the size of frequency components of interest. We call the matrix in Eq. (3) a

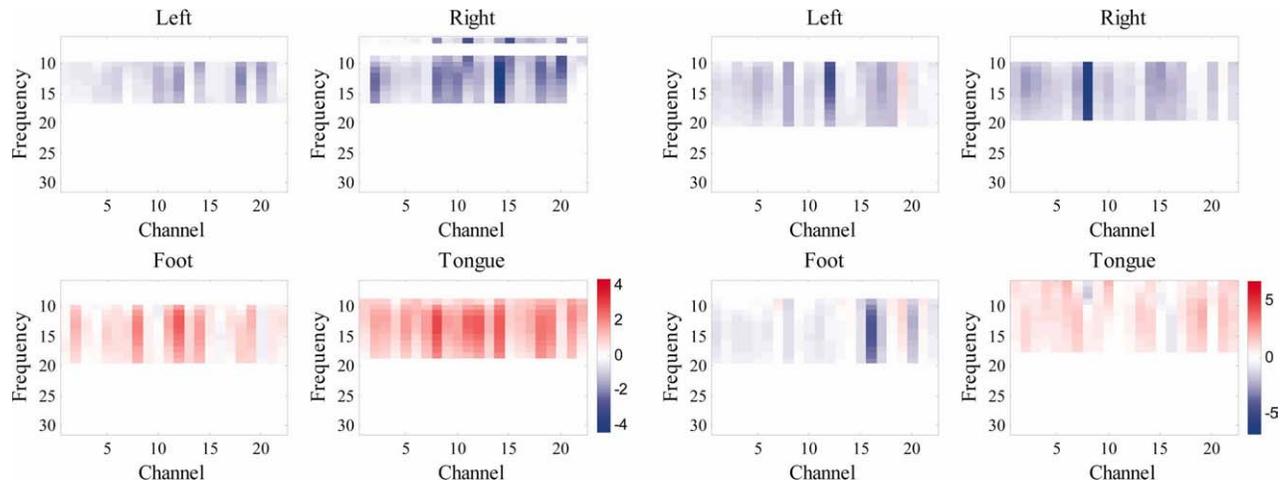


Figure 3. Examples of the channel-frequency map (CFM) for subject 1 (left) and subject 3 (right). The color-coded values represent a time-domain averaged out ERSP of each channel meaning ERD (blue) or ERS (red). The online color version provides a clearer view. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

channel-frequency map (CFM). Figure 3 shows examples of the CFM for subjects 1 and 3. The X_i^c in Eq. (4), a time-domain averaged ERSP of the c th channel, represents the mean amplitude of the ERD/ERS in an individual frequency component for the c th channel.

Unlike the P300-based BCIs (Salvaris and Sepulveda, 2009) or steady-state visual evoked potential-based BCIs (Cecotti, 2010), motor imagery-based BCIs modulate brain signals spontaneously. That is, it is highly unpredictable when the target-EEG signals are evoked. This unpredictability makes it hard to extract meaningful features, which results in a failure to build a classifier of good performance. From this point of view, the X_i^c defined in Eq. (4) allows us to find an informative frequency component by comparing the weight of each frequency component.

We compute the weight of the specific frequency component f' by normalizing the sum of the squared CFM_i over the channels with the sum of the squared CFM_i over both channels and frequencies as follows:

$$w_i(f') = \frac{\sqrt{\sum_c CFM_i(c, f')^2}}{\sqrt{\sum_f \sum_c CFM_i(c, f)^2}} \quad (5)$$

Here $w_i(f')$ can be considered as an intensity of the ERD/ERS for the frequency component f' . If an ERD/ERS weight is larger than a threshold, we believe that the corresponding frequency component is informative for i th class and include it in the set of the selected frequency components SF_i as follows:

$$SF_i = \bigcup_f \left(w_i(f) > \delta_i^f \right) \quad \forall f \in \{1, 2, \dots, F\} \quad (6)$$

where δ_i^f denotes a threshold, which in our experiments, we set as the mean of weights.

When consecutive frequency components are selected in Eq. (6), they compose a frequency band in the rest of our system. That is, the selected standoff frequency components or consecutive frequency bands can be considered as the filter bank in (Chin et al., 2009) but with different bandwidths and removal of uninformative

frequency components. It should be noted that the proposed method of frequency bands selection is a generic new technique and by no means limited to the motor imagery-based BCI applications.

C. Feature Extraction and Classification Methods.

For each of the selected frequency bands, we build an independent classification stream. In each stream, we first apply a bandpass filter over the range of the corresponding frequency bands for all channels except the EOG. We consider the sample points of the interval between 0.5 s and 2.5 s after onset of the stimulus. We then apply the CSP algorithm (Ramoser et al., 2000) using a one-versus-the-rest strategy to find optimal spatial filters. The number of spatial filters is set to 6 empirically. Once the set of spatial filters has been determined, we apply them to the training and test sets. We extract feature vectors of the logarithm of the variances on the spatially and spectrally filtered output signals.

The feature vectors are then transformed by a linear discriminant analysis, more specifically multiple discriminant analysis (Duda et al., 2001), for the increase of discriminability among classes. A SVM, which has proved to perform strongly in a number of real-world problems including BCI (Lotte et al., 2007; Rakotomamonjy and Guigue, 2008), is trained with the transformed data. Similar to the CSP algorithm, we train the SVM with a one-against-all approach.

As we have multiple streams, each of which may produce an independent class label for the given EEG data, it needs to make a decision based on the resulting labels. We propose a two-step decision strategy. The first step is based on a voting method as follows:

$$\hat{v} = \arg \max_v V(v) \quad (7)$$

where $V(v)$ represents the number of classifiers that output the class label v for the given EEG data. If there is a unique bin that receives the largest votes from the SVMs, we then classify the input EEG into the corresponding label without proceeding to the second step. Or, as a second step, we consider the confidence of each SVM. That is, if more than two classes have the same maximum votes, we choose the class label to which a distance from the given feature is the largest:

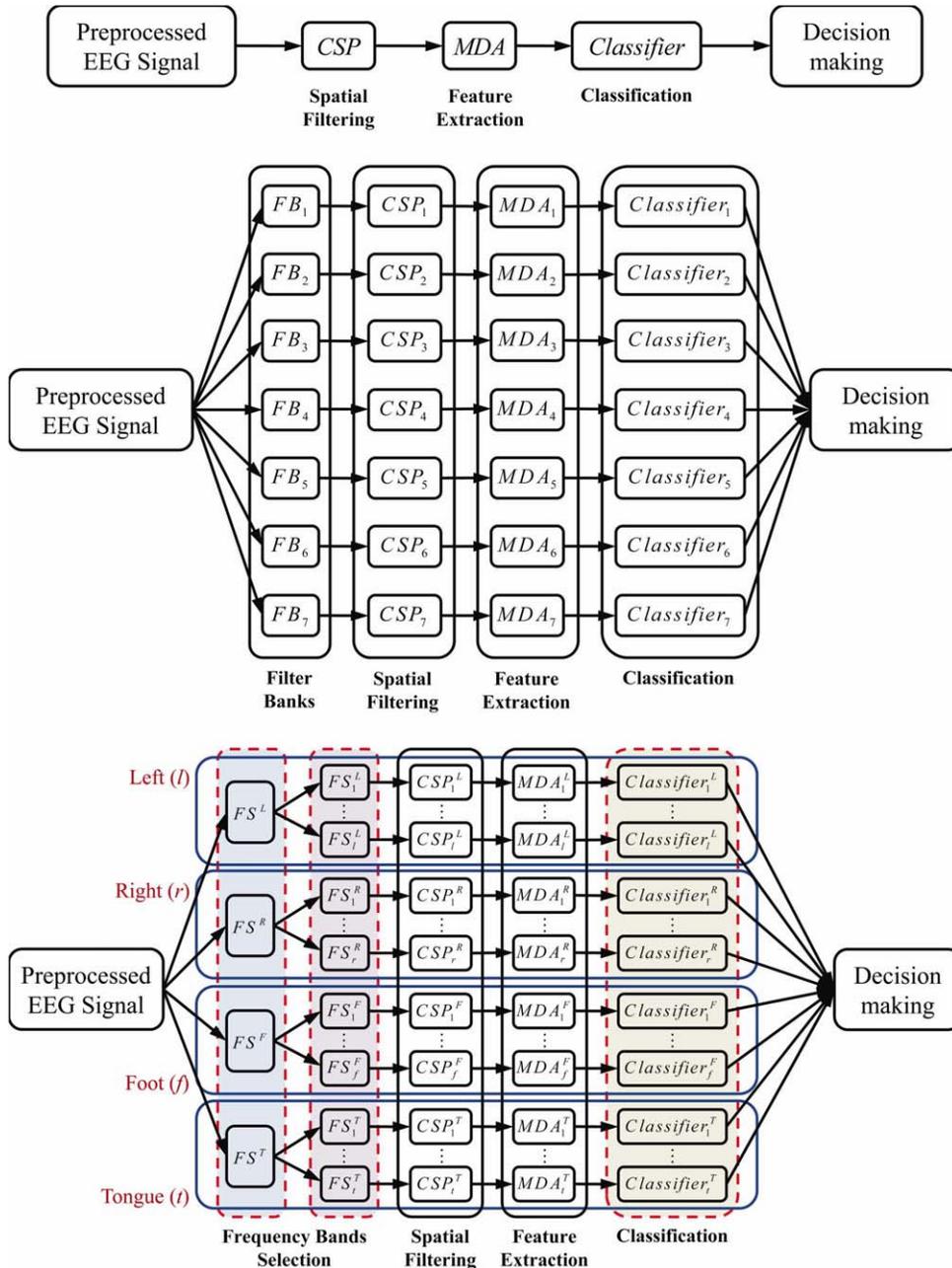


Figure 4. Diagrams of the competing models. (a) Baseline model (top), (b) filter bank based model (middle), and (c) the proposed model (bottom). The subscripts l , r , f , and t denote the number of frequency bands for the classes of left-hand, right-hand, foot, and tongue motor imagery, respectively. Frequency band (FB), frequency selection (FS), common spatial pattern (CSP), and multiple discriminant analysis (MDA). [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

$$\hat{i} = \arg \max_i D(i) \quad \text{iff } |\hat{v}| \geq 2, \quad \text{where } i \in \hat{v} \quad (8)$$

where $D(i)$ denotes a maximal distance between the feature vector and the hyperplane of a classifier that output a class label in \hat{v} , and $|\hat{v}|$ is a number of elements in the set \hat{v} . This strategy is from the rationale that the larger the distance from the hyperplane the more confident belonging to the class.

Figure 4c shows the operational flow of the proposed method for four motor imagery classifications, where the subscripts l , r , f , and t denote the number of frequency bands for the classes of left-hand,

right-hand, foot, and tongue, respectively. As we choose frequency bands of interest for each class individually, there exist $l + r + f + t$ independent streams. At the end of the system, we combine the outputs from the multiple stream SVM classifiers as depicted in Eqs. (7) and (8) to decide a class label for an input EEG.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. Designing Competing Models. To show the effectiveness of the proposed method, we build three competing models: baseline, Chin et al.'s filter bank, and the proposed frequency selection.

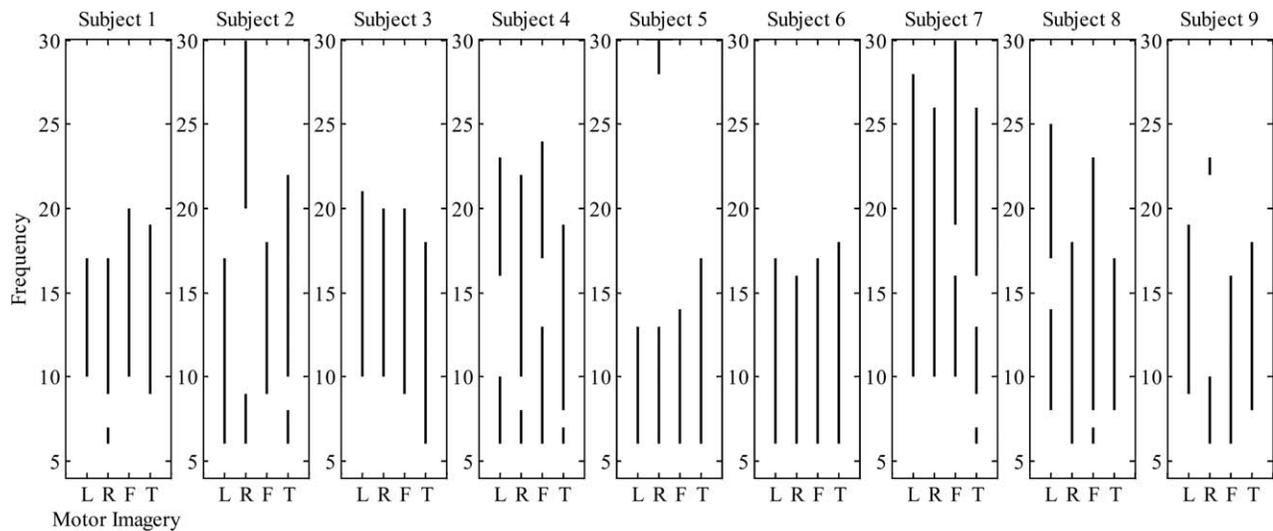


Figure 5. Selected frequency bands for each subject (L, left-hand; R, right-hand; F, foot; T, tongue).

While the baseline model deals with EEG signals bandpass-filtered between 5 Hz and 30 Hz covering μ and β rhythms, we should consider multiple bands for the other two models. In the filter bank and the proposed models, the ensuing operations are applied for each band individually, but we produce one class label by considering the outputs from multiple classifiers as explained in Section IV at the end of the system.

The CSP algorithm is applied to the preprocessed and bandpass-filtered EEG data to find optimal spatial filters. In our experiments, the number of spatial filters was set to 6 empirically, and applied equally to all the competing models. Feature extraction based on a multiple linear discriminant analysis and a classification with SVMs is followed. We used a nonlinear SVM with a Gaussian radial basis function. The diagram of the two competing models is presented in Figures 4a and 4b. Although a system flow of both the

filter bank in Figure 4b and the proposed method in Figure 4c looks similar, they are different in a way of selecting each frequency band. The frequency bands of a class can be in discord with those of others in the proposed method. In the filter bank model, we set the size of a filter bank to 4 Hz following Chin et al.'s (2009) work.

B. Cross-Validated Results. We performed cross validation for each subject by randomly selecting training data and using the rest for validation. We have distinct frequency bands for each class as illustrated in Figure 5. Although they are mostly ranging between 6 Hz and 20 Hz, it is clear that the bands are variable among classes and subjects. Figure 6 presents the averaged performances from 10 repetitions with the dataset during session 1 according to the changes of the training set size from 10 to 60. The performances are substantially heterogeneous among subjects, ranging from 31.67%

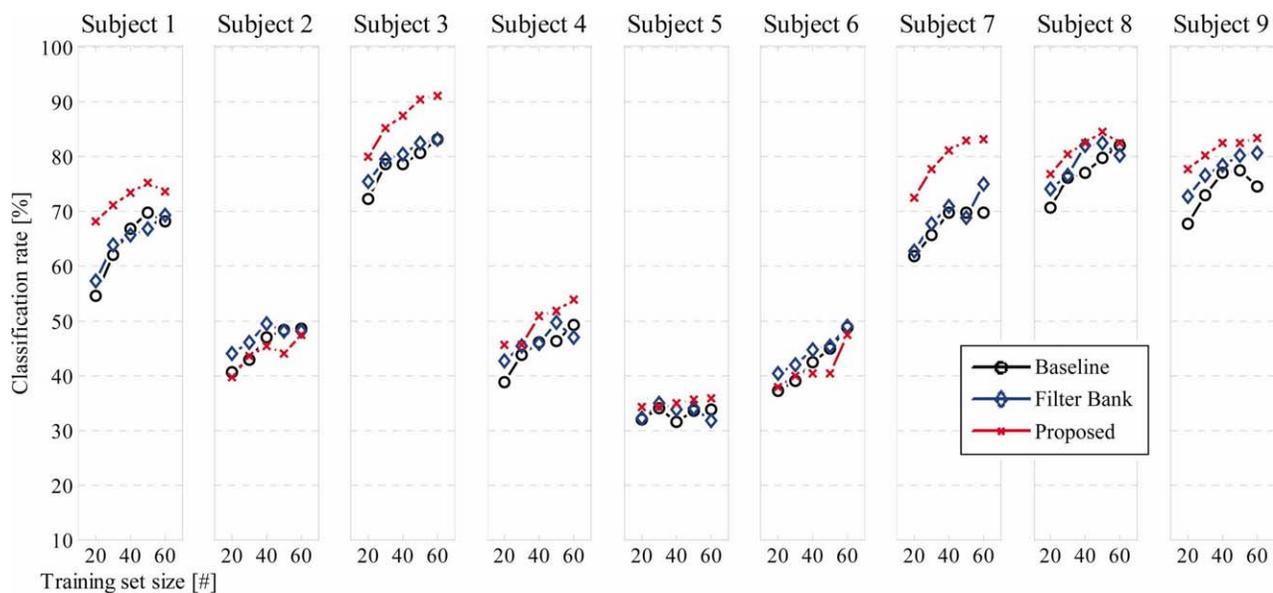


Figure 6. Cross-validated performances of the three competing methods for all subjects according to the changes of the training set size during session 1. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Table I. Summary of cross-validated performances with 60 training data per task for each method on a dataset of session 1.

	Baseline	Filter Bank	Proposed
Mean (%)	61.92	62.64	66.43
Standard deviation (%)	17.66	18.69	19.83

for subject 5 to 91.04% for subject 3 with 60 training trials per task. The proposed method showed the highest accuracy for seven out of nine subjects, whereas the filter bank-based model resulted in less than 1% superior to the proposed method for subject 2 and subject 6. A summary of the cross-validated performances showing the superiority of the proposed method is presented in Table I with standard deviations and the grand mean of 9 subjects for the competing methods.

C. Performances in Session-to-Session Transfer. The goal of the BCI Competition IV on the dataset II-a was to evaluate classification algorithms based on session-to-session transfer rate, using session 1 dataset for training and session 2 dataset for evaluation. In Table II, we summarize the performances of three competing methods. The proposed method outperformed the other methods for all subjects except for subject 2 when we used the EEG data of session 1 for training and the EEG data of session 2 for evaluation, and vice versa. From the comparison of the performances between the filter bank method and the proposed method, for which we have applied the same approach to making a decision, i.e., voting strategy from multiple classifiers, we can say that the proposed frequency bands selection has a more impact on classifying motor imagery than the method of building classifiers.

We also compare the best performances obtained by the proposed method with the performances of the three best competitors in the competition and other methods recently published in (Gouy-Pailler et al., 2010). For a fair comparison with the other methods, we use the criterion of the kappa score (Cohen, 1960), used in the competition. Table III summarizes the results. We can see that the proposed frequency bands selection method proved the best four out of nine subjects and presented the second highest kappa score on average among seven different methods. We visually investigated the ERSPs for the analysis of the low performance of subjects 2, 5, and 6. When compared with those of the subjects for whom the proposed method showed high accuracy, the ERD/ERS in ERSP

Table II. Mean classification rate (%) of three competing methods in terms of session-to-session transfer.

	From Session 1 to Session 2			From Session 2 to Session 1		
	Baseline	Filter Bank	Proposed Method	Baseline	Filter Bank	Proposed Method
Subject 1	67.26	66.25	75.66	60.52	63.51	76.11
Subject 2	41.32	37.26	40.63	29.51	39.24	32.92
Subject 3	72.47	75.31	79.86	66.60	70.94	80.42
Subject 4	45.80	50.28	56.74	37.95	45.17	45.38
Subject 5	33.44	34.97	36.53	29.17	34.03	42.29
Subject 6	37.36	36.77	37.74	36.15	44.83	46.30
Subject 7	64.24	66.53	80.45	54.72	65.38	72.54
Subject 8	69.79	72.61	79.24	52.47	61.60	62.60
Subject 9	67.29	67.71	75.03	65.87	71.69	73.82
Mean (%)	55.44	56.41	62.43	48.11	55.15	59.15

The training set size was set to 60 trials per motor imagery task.

Table III. Kappa scores of the best performance of the proposed method and three best competitors in BCI Competition IV (2008) and the methods of joint approximate diagonalization (JAD), common spatial pattern (CSP), and multi-segment JAD (MSJAD) presented in Gouy-Pailler et al.'s work (2010).

	Proposed Method	Three Best Competitors ^a			Gouy-Pailler et al. (2010)		
		1st	2nd	3rd	JAD	CSP	MSJAD
Subject 1	0.71	0.68	0.69	0.38	0.65	0.52	0.66
Subject 2	0.31	0.42	0.34	0.18	0.40	0.39	0.42
Subject 3	0.75	0.75	0.71	0.48	0.77	0.67	0.77
Subject 4	0.47	0.48	0.44	0.33	0.50	0.50	0.51
Subject 5	0.19	0.40	0.16	0.07	0.44	0.49	0.50
Subject 6	0.20	0.27	0.21	0.14	0.19	0.18	0.21
Subject 7	0.78	0.77	0.66	0.29	0.25	0.26	0.30
Subject 8	0.77	0.75	0.73	0.49	0.72	0.57	0.69
Subject 9	0.73	0.61	0.69	0.44	0.50	0.40	0.46
Mean	0.55	0.57	0.51	0.31	0.49	0.44	0.50

^aThe results as well as the methods produced them were detailed on the website of BCI Competition IV (2008) (<http://www.bbci.de/competition/iv/results/index.html>).

of these three subjects presented relatively small values. The proposed method failed to determine the informative frequency bands. Here, we should also note that the first and third best competitors applied bandpass-filtering and linear regression, respectively, to remove the artifacts in the dataset.

VI. CONCLUDING DISCUSSIONS

Brain rhythms related to the imagination of body-parts movement are highly variable over different stimuli and subjects. Designing a motor imagery-based BCI system requires a time-consuming process to select frequency components for each set of mental tasks to be classified and for each subject from visual inspection. Unlike previous approaches of selecting frequency bands manually or generally setting a broad band, we propose a data-driven method of subject and class specific frequency band selection for multiclass motor imagery classification with the time-frequency map analysis using ERSP (Makeig, 1993). In each of the selected frequency bands, the classification process operates individually and a label for an input EEG is determined by considering the outputs from multiple classifiers together at the end with a two-step decision strategy.

We demonstrated the performance of three competing methods on a public dataset of BCI Competition IV II-a of four motor imageries: left-hand, right-hand, foot, and tongue. The performance of the proposed method outperformed a baseline model that considered a wideband (between 5 Hz and 30 Hz) EEG and a filter bank-based model that followed Chin et al.'s (2009) approach with non-linear SVMs. Apart from the higher accuracy in classification, the proposed method has an advantage of eliminating a time-consuming calibration process of determining frequency bands for each subject.

From the visual inspection of the proposed CFM, we can clearly see that there exist class specific frequency bands—highly responsive to the corresponding motor imagery—and subject specific bands, different bands for different subjects in the same motor imageries. Finally, we would like to remark that the proposed CFM and multiple stream-based classification methods are not limited to the motor imagery classification, but also applicable to other EEG-based brain computer interface, such as P300-based word speller.

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