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ORIGINAL ARTICLE

Spatio-spectral filters for low-density surface electromyographic signal classification

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Abstract In this paper, we proposed to utilize a novel spatio-spectral filter, common spatio-spectral pattern (CSSP), to improve the classification accuracy in identifying intended motions based on low-density surface electromyography (EMG). Five able-bodied subjects and a transradial amputee participated in an experiment of eight-task wrist and hand motion recognition. Low-density (six channels) surface EMG signals were collected on forearms. Since surface EMG signals are contaminated by large amount of noises from various sources, the performance of the conventional time-domain feature extraction method is limited. The CSSP method is a classification-oriented optimal spatio-spectral filter, which is capable of separating discriminative information from noise and, thus, leads to better classification accuracy. The substantially improved classification accuracy of the CSSP method over the time-domain and other methods is observed in all five able-bodied subjects and verified via the cross-validation. The CSSP method can also achieve better classification accuracy in the amputee, which shows its potential use for functional prosthetic control.

Keywords EMG · CSSP · Spatio-spectral filter

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1 Introduction

Surface electromyography (EMG) has been proved to be one of the major neural control sources for human computer interface (HCI) by its numerous applications, such as muscular diseases diagnoses [4] and prosthetic control [3]. Researchers have also successfully used surface EMG signals to control computers [29], robots and wheelchairs [2]. EMG signals are generated by the electric activities of the contraction of muscle fibers, and, thus, they are able to provide valuable information on the muscle condition. In general, surface EMG signals generated from different motions exhibit different characteristics in the time, spectral, or spatial domain, and hence, they have been widely used to recognize intended motions, say, in prosthetic control. EMG characteristics are usually presented in the time or spectral domain, such as the commonly used time-domain (TD) features [21], Autoregressive (AR) features [1, 17], and spectral magnitude averages (SMA) [24].

Surface EMG signals are always contaminated by large amount of noises from various sources, such as inherent noise from equipments, ambient noise, and motion artifacts [7]. In addition, the complex muscle distribution makes the crosstalk problem inevitable in surface EMG recording [6]. As a result, pre-processing of surface EMG is crucial for subsequent feature extraction and classification. An effective pre-processing method can separate discriminative EMG information from noise for a better classification accuracy. Spectral filtering is a conventional way to filter out unwanted noise, because discriminative EMG information is usually dominant in some specific frequency bands. Another important type of filtering techniques is spatial filtering, which addresses the noise and crosstalk problems by making use of spatial distribution information of EMG data. Various spatial filters, such as one-ring differential system [5, 12], longitudinal and transversal single and double differential [13], Laplacian filter [27, 28], inverse binomial filter [8] and inverse rectangle filter [8], have been proposed for EMG signal processing, and many of them have shown improvements in noise reduction and feature enhancement [20].

Similar to the cases in EMG research, spatial filtering also plays an important role in electroencephalogram (EEG) research. A well-designed spatial filter could effectively improve the accuracy and information transform rate of EEG-based brain computer interface (BCI) systems. Recently, a novel spatial filter, common spatial pattern (CSP), has shown an excellent performance in EEG-based BCI systems [27]. By solving a generalized eigenvalue problem, the CSP filter removes the signal's strong correlation among the original axes, and the distributions are maximally dissimilar along the new axes. The CSP method separates multi-channel EEG signals into a series of projected vectors and the variances of the projected vectors are used as features for classification.

Several variants of CSP have been developed and the most important one is the common spatio-spectral pattern (CSSP), which was developed by Lemm et al. [23]. It embeds a finite impulse response (FIR) spectral filter into CSP to produce a spatio-spectral filter. Because CSSP simultaneously performs filtering in the spatial domain and the spectral domain, it can more effectively reinforce discriminative signal features than the CSP method.

In [18], Hahne et al. firstly used the CSP method in EMG signal processing and observed an improved classification accuracy and higher robustness than the commonly used TD method (with bipolar spatial filter). However, a high-density electrode arrangement is usually needed to guarantee a better performance of the CSP spatial filter [14]. In [18], 22 monopolar surface EMG electrodes were used. In practical applications, the high-density electrodes arrangement (>10 channels) will often bring some problems for prosthetic control. Firstly, too many electrodes will increase the production cost and power consumption of prosthetic. Secondly, high-density electrodes will make the prosthetic installation more complex and time-consuming for amputees. Thirdly, more electrodes also increase the incidence of failure of the system, making the prosthetic unstable. As far as we know, there is no report on CSP's successful application to low-density (<10 channels) electrode layout, no matter in EEG study or EMG study. Another limitation of the CSP application to EMG is that the important discriminative spectral domain characteristics of surface EMG are overlooked. Spectral characteristics of surface EMG provide alternative and complementary information of muscle conditions, and, therefore, including spectral characteristics is expected to improve the accuracy in identifying intended motions.

In this work, we investigate the CSSP spatio-spectral filter for classification of surface EMG signals in a low-density channel layout. The CSSP method (1) employs an additional spectral filter to separate discriminative EMG features in the spectral domain, and (2) increases the number of channels by generating "artificial" channels with delayed signals to partially overcome the limitation of low-density channels. To our knowledge, this study is the first attempt to apply CSSP method in EMG analysis.

Five able-bodied subjects and a transradial amputee participated in an experiment with eight tasks. Six bipolar electrodes were used for surface EMG signal collection, and they were placed uniformly at 1/3 of the distance from elbow to wrist. The CSSP method is employed to perform a spatio-spectral filtering and to extract features for classification of eight-motion tasks. The performance of CSSP largely depends on its accompanied parameters and the parameter selection for EEG has been well studied [23]. However, because EMG and EEG have quite different characteristics [15], the conventional parameter setting of CSSP in EEG could not be directly applied to EMG. Therefore, this study discusses how the parameter setting influences the classification accuracy and how to select the parameters. Linear discriminant analysis (LDA) was used to classify eight tasks from EMG features extracted by CSSP. The superiority of the CSSP method is illustrated by comparisons with conventional temporal (TD), spectral (SMA), and spatial (CSP) EMG analysis methods.

In the rest of the paper, Sect. 2 gives an introduction of the experimental setup and the CSSP method. In Sect. 3, the performance of the CSSP method is compared with TD, SMA and CSP method. The discussion and the conclusions follow in Sects. 4 and 5, respectively.

2 Methods

2.1 Experiment setup

Six subjects participated in the experiment, including five able-bodied persons and a transradial amputee. All subjects were right handed. Each subject was given the written informed consent prior to the experiment. The experiments are in accordance with the declaration of Helsinki. Ethical approval of the study was sought and obtained from the Bioethics Committee, School of Biomedicine Engineering, Shanghai Jiao Tong University (ethic approval number BM(E)2012045).

The EMG signals were collected by ME6000 (MEGA Electronics Ltd, Finland) with built-in 305× amplification, a 3 dB bandpass of 8–500 Hz, a 14-bit A/D converter and a sampling rate of 1,000 Hz. Six bipolar electrodes were distributed uniformly at 1/3 of the distance from elbow to wrist. Figure 1 shows the positions of the electrodes for both able-bodied persons and the amputee.

During the experiment, the subjects were instructed to perform eight motions, which were wrist flexion and extension, hand grasp and open, supination and pronation, radial flexion and ulnar flexion (as shown in Fig. 2). The experiment included 10 runs. In each run, the subjects performed each motion for 10 s with approximately 40 % force. Between two runs, subjects would have a break as they want. Each subject finished the experiment in less than 20 min. EMG pattern classification was conducted within 100 ms sequential analysis windows from 3 to 8 s for each motion. Hence, 4,000 feature samples were collected for each subject in all.

Remark It should be noted that, in [18], the authors applied CSP on monopolar EMG data, because monopolar data generally contain more information than bipolar data. However, monopolar recording is not available in most commercial EMG systems. In this study, the hardwired bipolar recording is provided by ME6000, which can only output bipolar data. Compared with monopolar recording, hardwired bipolar recording has higher CMRR, higher input impedance and stronger DC signal suppression and, thus, provides better-quality signals than numerical bipolar signals. This study shows that the CSSP method is suited to analyze bipolar EMG data.

2.2 Existing EMG feature extraction methods

To make an overall understanding about the problem in EMG recognition, we firstly review three conventional methods, TD, SMA, and CSP, which extract EMG features in temporal, spectral and spatial domain, respectively.

1. Time-domain (TD)
   The TD features were originally proposed by Hudgins et al. [21], where the continuous EMG signals were segmented into multiple frames and TD features were extracted from each frame. The EMG signal from one

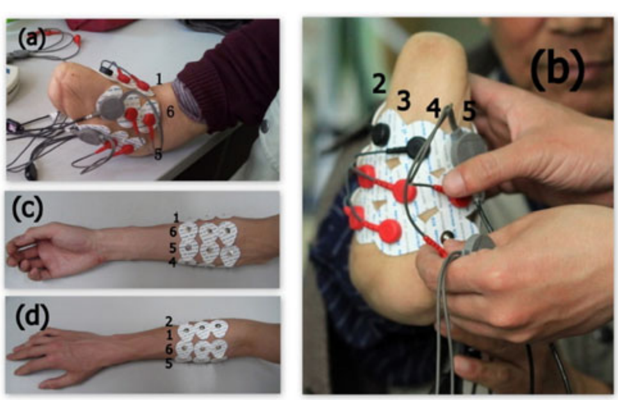

Fig. 1 The positions of six pairs of EMG sensors for amputee (**a**, **b**) and able-bodied (**c**, **d**) subjects

   channel can be represented as a finite time sequence $(x_1, x_2, \ldots, x_t)$, where t is the number of samples in a frame. TD feature set for this time sequence includes four statistics, which are

   (1) Mean absolute value (MAV)

$$\mathrm{MAV} = \frac{1}{t}\sum_{i=1}^{t}|x_i|, \tag{1}$$

   (2) Number of zero crossings (ZC)

$$\mathrm{ZC} = \sum_{i=2}^{N}\mathrm{sgn}(-x_i x_{i-1}), \tag{2}$$

   (3) Waveform length (WL)

$$\mathrm{WL} = \frac{1}{N-1}\sum_{i=2}^{N}|x_i - x_{i-1}|, \tag{3}$$

   (4) Number of slope sign changes (SSC)

$$\mathrm{SSC} = \sum_{i=3}^{N}\mathrm{sgn}[-(x_i - x_{i-1})(x_{i-1} - x_{i-2})] \tag{4}$$

   where $\mathrm{sgn}(x)$ is a sign function, defined as

$$\mathrm{sgn}(x) = \begin{cases} 1 & \text{if} \quad x > 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

   The effectiveness of the TD feature set in EMG study has been repeatedly proven in the literature [19, 21, 31]. In [11], Englehart et al. showed that the TD feature set is powerful for continuous EMG classification.
2. Spectral magnitude averages (SMA)
   The SMA feature provides spectral information of EMG signal in different frequency bands. As proposed by Du [9], SMA is an improvement of the Power Spectral Density (PSD) method. Considering the high variance of the PSD features, the SMA method defines the spectral-based features as averaged PSD values within frequency intervals. The whole frequency span is divided into a series of equidistant bands, and the averaged spectral magnitude within each band is calculated. To make better classification accuracies of the SMA method, all the features are generally logarithm transformed. Although the SMA method is not as often used as the TD method in EMG signal recognition, it provides alternative and complementary information of the signal in the spectral domain.
3. Common spatial pattern (CSP)
   The CSP method was proposed by Fukunaga [16] and was used to extract the abnormal components from EEG by Koles [22]. Later, CSP was successfully applied by Ramoser et al. [26] to motor imagery based

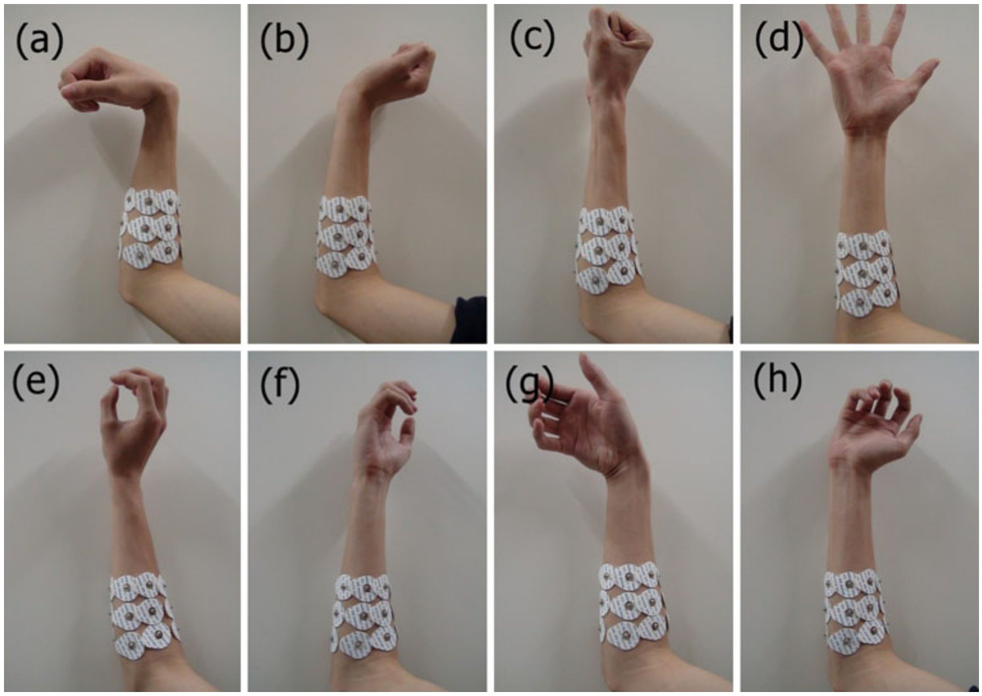

Fig. 2 Eight motions for every subject to perform, which are wrist flexion and extension, hand grasp and open, supination and pronation, radial flexion and ulnar flexion from **a** to **h**

BCI systems and it was shown that the CSP can considerably improve the classification accuracy of the motor imagery BCI.

Consider a two-class classification problem. Let $\mathbf{X_c} \in R^{n \times t}$ denotes one trial of signal with class c ($c = 1$ or 2), where n is the number of channels (i.e., recording electrodes) and t is the number of samples per channel. The CSP method solves the following generalized eigenvalue equation

$$\langle \mathbf{X_1 X_1}^T \rangle \mathbf{w} = \lambda \langle \mathbf{X_2 X_2}^T \rangle \mathbf{w} \tag{6}$$

to find the generalized eigenvector or the projection vector $\mathbf{w}$ to maximize the variance difference between two classes of trials, where $\langle \cdot \rangle$ is the averaging operator for trials in the same class and λ is the generalized eigenvalue. The projection vector w is also called as a spatial filter. In general, only a few pairs of $\mathbf{w}$ corresponding to the largest and smallest eigenvalues λ are selected and the log-transformed variances of the projected vectors, i.e.,

$$f = \log(\mathrm{var}(\mathbf{wX})), \tag{7}$$

are used as features for classification.

2.3 CSSP

The main idea of CSSP method is to embed an FIR filter into the CSP filter. Consider the delayed signals $(\delta^{\tau}\mathbf{X}, \delta^{2\tau}\mathbf{X}, \ldots, \delta^{m\tau}\mathbf{X})$ as the new channels, i.e.,

$$\hat{\mathbf{X}} = \begin{pmatrix} \mathbf{X} \\ \delta^{\tau}\mathbf{X} \\ \vdots \\ \delta^{m\tau}\mathbf{X} \end{pmatrix}, \tag{8}$$

where τ is the delay constant, m is the order of the FIR filters. By solving the new generalized eigenvalue equation

$$\langle \hat{\mathbf{X}}_1 \hat{\mathbf{X}}_1^T \rangle \hat{\mathbf{w}} = \lambda \langle \hat{\mathbf{X}}_2 \hat{\mathbf{X}}_2^T \rangle \hat{\mathbf{w}}, \tag{9}$$

several pairs of $\hat{\mathbf{w}}$ corresponding to largest and smallest eigenvalues λ can be obtained. With the project vector $\hat{\mathbf{w}} = (\hat{\mathbf{w}}^0, \hat{\mathbf{w}}^{\tau}, \hat{\mathbf{w}}^{2\tau}, \ldots, \hat{\mathbf{w}}^{m\tau})$, we have the projected signal

$$\hat{\mathbf{Z}} = \hat{\mathbf{w}}^0\mathbf{X} + \hat{\mathbf{w}}^{\tau}\delta^{\tau}\mathbf{X} + \cdots + \hat{\mathbf{w}}^{m\tau}\delta^{m\tau}\mathbf{X} \tag{10}$$

$$= \sum_{k=1}^{n} \gamma_k \left(\frac{\hat{w}_k^0}{\gamma_k}\mathbf{X}_k + \frac{\hat{w}_k^{\tau}}{\gamma_k}\delta^{\tau}\mathbf{X}_k + \cdots + \frac{\hat{w}_k^{m\tau}}{\gamma_k}\delta^{m\tau}\mathbf{X}_k \right) \tag{11}$$

where

$$\gamma_k = \frac{\hat{w}_k^0}{|\hat{w}_k^0|}\sqrt{\hat{w}_k^{0^2} + \hat{w}_k^{\tau^2} + \hat{w}_k^{2\tau^2} + \cdots + \hat{w}_k^{m\tau^2}}. \tag{12}$$

$(\gamma_1, \ldots, \gamma_n)$ is the spatial filter, and $(\hat{w}_k^0/\gamma_k, \hat{w}_k^{\tau}/\gamma_k, \ldots, \hat{w}_k^{m\tau}/\gamma_k)$ is the FIR filters for channel k. Similarly, the log-transformed feature,

$$\hat{f} = \log(\mathrm{var}(\hat{\mathbf{w}}\hat{\mathbf{X}})), \tag{13}$$

is used for classification.

It is worth noting that, with insufficient number of features, both CSP and CSSP have a tendency to overfit, i.e., to learn the noise in the training set rather than the signal. CSSP is more easily overfitted because it involves more channels than CSP. The overfitting problem of CSP could be serious in EEG research, where the time window used for feature extraction is usually long (typically longer than 3 s) and, thus, the number of feature samples is small. In EMG research, the time window used for feature extraction is generally short (say, 100 ms), and thus, the number of EMG feature samples will be large. Hence, the overfitting problems will not be so serious in EMG.

Furthermore, the performance of CSSP strongly depends on several parameters: the order of the FIR filter, m, and the delay constant, τ [23], and the number of the CSSP components [30]. In this paper, we also studied the parameters selecting in CSSP. Firstly, the number of components used in CSP and CSSP will be discussed. And then under the fixed number of components, we will explore effect of the FIR filter, m, and the delay constant, τ in CSSP. The results will be presented in Sect. 3.

2.4 Multi-class CSP/CSSP classification

Aiming to recognize right- and left-hand motor imagery in BCI, the original CSP/CSSP methods are limited to solve the two-class problem. To deal with the multi-class classification in this work, we adopted the One vs. One (OvO) strategy (performing two-class CSP and CSSP on all possible combinations of classes) for both CSP and CSSP methods. Hence, for the eight-motion classification problem, there are $C_8^2 = \frac{8\times(8-1)}{2} = 28$ combinations in all. Linear discriminant analysis (LDA) [10] was employed as the classifier, which is also widely used to discriminate EEG signal for different imagery motions after CSP and CSSP filtering [26]. All the results came from the average of fivefold cross-validation.

3 Results

Table 1 shows the classification results of TD, SMA, CSP and CSSP methods. For SMA method, the frequency range evaluated is from 0 to 500 Hz and it is equally divided into 10 bands for classification. For both CSP and CSSP method, six components are used and the OvO multi-class strategy is adopted. In CSSP method, the delay $\tau = 1$ ms, and the order of the filter m is limited to 3. Hence, the feature dimensions are 24 (4 statistics $\times$ 6 channels) for TD, 60 (10 bands $\times$ 6 channels) for SMA, 168 ($C_8^2 = 28$ combinations $\times$ 6 components) for CSP and 168 ($C_8^2 = 28$ combinations $\times$ 6 components) for CSSP.

Table 1 Classification errors rate (%) of the six subjects with different feature sets

Subject	Method			
	TD	SMA	CSP	CSSP
A	1.95	1.27	3.08	**0.93**
B	2.80	1.23	6.38	**0.65**
C	4.48	5.25	6.75	**1.98**
D	2.53	1.73	3.73	**1.15**
E	0.45	**0.03**	0.45	**0.03**
F*	13.25	12.08	11.13	**9.35**
Mean	4.24	3.60	5.25	**2.35**

The results of using 3, 4 and 5 channels are averaged across all possible combinations of 3, 4 and 5 channels from 6 channels. * For CSP with 3 channels, the covariance matrix in LDA is singular in some conditions. The results with fewer channels (1 or 2) are not presented because the covariance matrix in the LDA classifier is easier to be singular for CSP. The best results are marked in bold

Table 2 Classification errors rate (%) with different number of channels

Channels	3	4	5	6
TD	13.32	8.25	5.68	**4.24**
SMA	9.13	5.84	4.33	**3.60**
CSP	N.A.*	10.29	7.10	**5.25**
CSSP	7.06	4.53	3.25	**2.35**

On these data, the CSSP feature set outperforms all other feature sets. The amputee is marked by asterisk. The best results are marked in bold

For TD method, the health subjects could achieve good performances with the error rate less than 5 %. However, the amputee's error rate (13.25 %) is much lower. The results from SMA are better than TD in all the subjects except Subject C. Compared with the results with high-density electrode arrangement [18], the performance of CSP is degraded seriously in low-density electrode condition. With limited number of electrodes, CSP could not perform better than TD in all the health subjects. But the error rate of the amputee by CSP is 2 % better than that of TD. In contrast, CSSP is more suitable for low-density EMG detection. The classification errors of CSSP method are always the lowest among the four methods under the test for both able-bodied persons and the amputee. We also test four classification methods on data from less number of channels. It can be clearly seen from Table 2 that the classification error gradually decreases with the number of channels for all four classification methods. Moreover, CSSP always provides the best result among four classification methods. Based on the results, we used all available six channels in CSSP.

Table 3 The pairwise classification errors for TD, SMA, CSP and CSSP method (from left to right, top to bottom in each cell) with the eight motions listed in Fig. 2

TD SMA CSP CSSP	(b) Wrist extension		(c) Hand grasp		(d) Hand open		(e) Supination		(f) Pronation		(g) Radial flexion		(h) Ulnar flexion	
(a) Wrist flexion	0.0	0.0	0.3	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.7
	0.0	0.0	0.7	0.5	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.4	1.0
(b) Wrist extension			0.0	0.0	1.0	0.0	0.4	0.0	0.1	0.0	0.0	0.0	0.0	0.0
			0.0	0.0	0.6	2.0	2.5	2.3	0.0	0.0	0.1	0.0	0.0	0.0
(c) Hand grasp					2.3	5.8	0.5	2.9	0.9	6.3	0.6	3.2	3.1	5.3
					0.4	0.0	1.1	0.2	0.8	0.1	0.0	0.1	1.5	0.6
(d) Hand open							0.4	0.3	*0.7*	*0.8*	0.9	0.2	0.2	0.0
							6.0	0.7	*8.4*	*0.2*	3.2	0.8	0.0	0.0
(e) Supination									0.2	0.0	0.3	0.2	0.0	0.4
									1.1	0.2	2.7	0.1	0.0	0.0
(f) Pronation											0.1	0.0	0.4	0.5
											0.3	0.0	0.1	0.3
(g) Radial flexion													0.0	0.0
													0.0	0.0

We now discuss the optimal selection of parameters used (number of CSSP components, filter order, and delay constant) in CSSP. In summary, these parameters are selected from a set of candidates as the values with the optimal classification results.

1. *Optimal selection of number of CSSP components:* Due to the fact that the only 6 channels of EMG signals were collected in the experiment, the maximum number of components available is 6 for CSP method. Meanwhile, with the filter order $m = 3$, the maximum number of components for CSSP method is 24 ($(m + 1) \times 6$ channels). The CSP and CSSP results with different numbers of components are shown in Fig. 3. The averaged classification errors of CSP method decreases as more components are selected. For CSSP method, more components (more than 6 components) would make the result better for the amputee, but not any better for the other subjects. Considering a higher computational complexity for more components, 6 components are selected for CSSP method. For different orders of the FIR filter or different delay constant τ, the features from 6 components always provide the best results or the results close to the best.
2. *Optimal selection of filter order and delay constant:* Figure 4 summarizes the averaged classification errors with different orders of the FIR filter m and the delay constant τ when 6 CSSP components are selected. For each subject with all different orders of the FIR filter, the delay $\tau = 1$ ms always performs better than the others. A higher-order filter would provide more flexible magnitude response, but it would also decrease

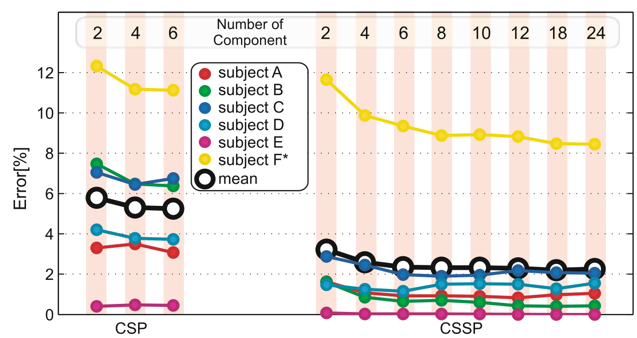

Fig. 3 The classification errors of CSP and CSSP methods with different numbers of components (labeled on the *top*). The results for each subject are marked in *different colors*. And the averaged errors are marked in *black* (color figure online)

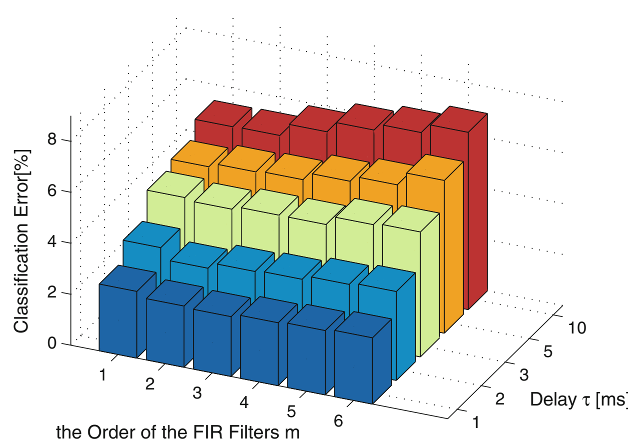

Fig. 4 Performance comparison of CSSP with different delay constant τ and the order of the FIR filter m

the generalization of the CSSP method. Here, as shown in Fig. 4, the third-order FIR filter has the best performance for delay constant $\tau = 1$ ms. With the introduction of the delayed signals, the length of the signal would be reduced from l to $l - m \times \tau$. Hence, for CSSP method, the length of the signal is 97 ms with a third-order FIR filter and $\tau = 1$ ms.

4 Discussion

The results presented in the previous section illustrated the improved performance of the CSSP method over other three methods. In this section, we illustrate how the CSSP spatio-spectral filtering is able to have an improved classification accuracy than the CSP method.

Subject C is taken as an example because this subject has the worst performance among five able-bodied subjects and, thus, the classification error is more evident for comparison. The eight-motion classification problem is divided into 28 two-class problems. Table 3 shows the classification errors of the four methods for the 28 two-class problems on Subject C. The parameter setting is the same as it is in the last section. However, for these two-class problems, the number of CSP or CSSP features is reduced to 6, which is equal to the number of components.

As illustrated in Table 3, most motions could be distinguished easily from each other. A special case, motion (d) versus (f), is italicized in Table 3, in which more than 8 % classification error is made by CSP method. Figure 5 depicts the spectral information (obtained using the Welch's method [25]) of 6-channel EMG signals in the special case. All these motions show similar spectral patterns in the frequency domain. The dominant energy of the origin EMG signal is in the range of 20–150 Hz. The bar charts below are the classification accuracies of the SMA method in each frequency band. The six panels in the right column of Fig. 5 show the frequency response of the FIR filters embedded in CSSP for each channel in the CSSP components.

Based on the results shown in Fig. 5, the advantages and disadvantages of the four methods are discussed as follows.

1. TD: MAV is an estimate of the mean amplitude of the EMG signals and ZC is a simple measure of the frequency. By making a difference in consecutive samples, the statistics WL and SSC can make an indirect reflection about the amplitude and frequency in high-frequency domain. Hence, the TD feature set provides a relatively comprehensive measure of EMG amplitude and frequency. Although the TD method does not take advantage of the spatial information and therefore could not provide the best results in the four methods, its stability and simplicity make it commonly used for EMG signal recognition.

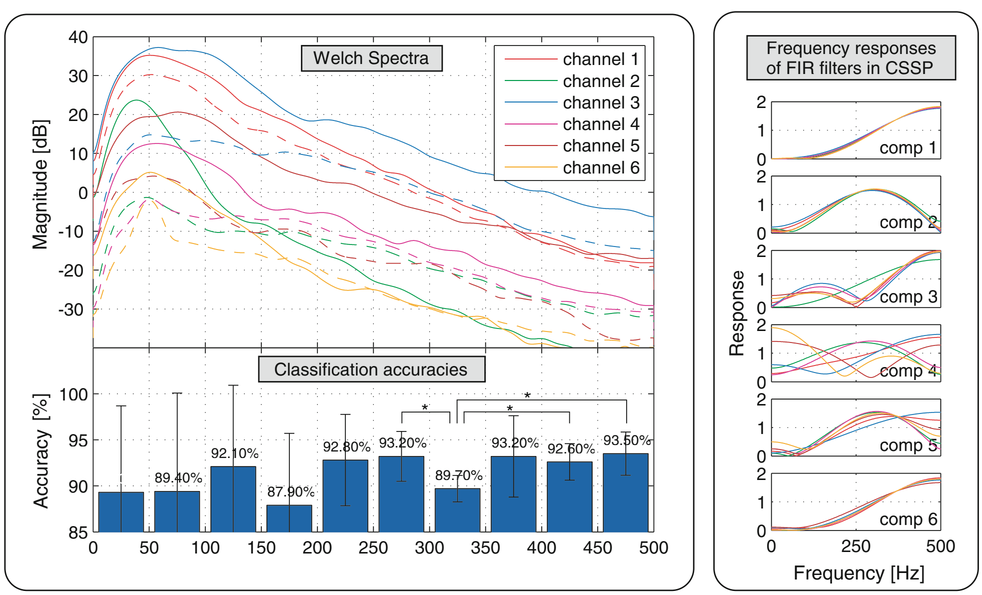

Fig. 5 *Left panel* the Welch's spectral estimates of surface EMG signals for motions (d) and (f), which are plotted in *solid* and *dash lines* respectively. *Different colors* denote different channels and the *bar chart* below shows the classification accuracies of different frequency bands with their standard deviations in the SMA method. *Asterisk* denotes that two frequency bands have significantly different classification accuracies ($p < 0.05$; paired two-sample t test). *Right panel* the frequency responses of FIR filters for each channel in the components made by CSSP method. *Different colors* denote different channels. In each component, 24 coefficients contain the information of 6 FIR filters for 6 channels, see Eq. (11) (color figure online)

2. SMA: As compared in Sect. 3, the SMA method could provide higher classification accuracy than the TD method in the eight-task problem for almost all the subjects except Subject C. In Table 3, the performance of SMA is quite unstable. SMA performs quite well in most two-class classification cases, but a large error rate was made by SMA when motion (c) or (h) is to be distinguished from other motions. In the special case of (d) versus (f), it can be clearly seen that the SMA method shows high classification accuracy in the middle-frequency band (200–300 Hz) and the high-frequency band (350–500 Hz), which implies that the EMG features in these frequency bands are more discriminative.
3. CSP: For CSP method, the limitation of channel number degrades its performance, which is not as effective as TD method in most cases. In addition, the components extracted by the spatial filters generally have the same energy distributions as the original EMG signals. In the conditions that the difference of the two motions is mainly in the dominant energy frequency band (20–150 Hz), the amplitude type features provided by the CSP method might have good performance. However, two motions may be better discriminative in frequency bands other than the dominant band. As seen in Fig. 5, the motions (*d*) and (*f*) are mainly distinguished in the middle- (200–300 Hz) and high-frequency bands (350–500 Hz), which do not coincide with the dominant energy frequency band (20–150 Hz). As a result, a large classification error of 8.4 % is made by the CSP method. Therefore, overlooking frequency characteristics of EMG is an inherent limitation of the CSP method.
4. CSSP: As an improvement of the CSP method, the CSSP method takes the frequency characteristics into account by automatically selecting both the spatial and spectral filters to maximize the difference between two classes. As shown in Fig. 5, most FIR filters embedded in CSSP have high-frequency responses in the middle- (200–300 Hz) and high-frequency bands (350–500 Hz), where the two motions are more discriminative. That is to say, by embedding high-pass FIR filters in the CSSP method, highly discriminative features in some specific frequency bands are retained while less-discriminative features in other frequency bands are restrained. Consequently, the CSSP method has a substantially lower classification error than the CSP method (CSSP: 0.2 %; CSP: 8.4 %) in this special case. More generally, the CSSP method adaptively designs FIR filters to keep highly discriminative features for classification, which explains its improved performance than the CSP method.

5 Conclusions

This paper makes the first attempt to apply the CSSP method in the problem of surface EMG classification, which could provide a joint spatio-spectral filter for better discriminability.

In the spatial domain, CSSP can automatically design a spatial filter to remove the signal's strong correlation and separate the signals maximally, which makes up the shortages of the fixed spatial filter, such as the bipolar differential. The CSP method could also provide well-designed spatial filter in a high-density electrode condition. But the performance of CSP is seriously degraded in the low-density electrode condition. By increasing the number of channels through generating "artificial" channels with delayed signals, CSSP would achieve satisfactory results in low-density EMG recognition.

In the spectral domain, we found that overlooking frequency characteristics of EMG is an inherent limitation of the CSP method. Using the CSSP method, the adaptively designed FIR filters could enhance highly discriminative features in some specific frequency bands and restrain the others to improve the performance.

Experimental results show that the CSSP method can achieve improved classification accuracy than the conventional methods in all five able-bodied subjects and one amputee. The CSSP method is expected to find applications in human–computer interaction such as functional prosthetic control.

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