Signal Processing for Brain-computer Interface: Enhance Feature Extraction and Classification

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***Abstract*— In this paper we present a new scheme for brain signal processing and classification for electroencephalogram based brain-computer interfaces, by emphasizing the extraction of space-time-frequency feature as well as the combination of classifiers. In particular, we use wavelet packets as a time-frequency analysis tool and employ sparse component analysis to recover source components in the brain signals. We subsequently apply multi-class common spatial pattern filters to the signals and thus obtain important space-time-frequency features for discrimination. Furthermore, a Bayesian method is developed to boost the system, by combining multiple support vector machines in a probabilistic way. We have tested the proposed scheme on real multi-class motor imagery signals, and its efficacy has been demonstrated.**

I. INTRODUCTION

Brain-computer interface (BCI) is an emerging technology which aims to convey people's intentions to the outside world directly from their thoughts [1]. It is especially appealing to severely paralyzed patients, since motor ability is no longer a prerequisite for this communication. It also offers a promising tool for normal people to enhance their communications with computers.

In the past few years, the technology has been receiving increasing attention from neurophysiologists as well as engineers from the signal processing community. Considerable efforts have been put to the study of electroencephalogram (EEG) signals particularly. The EEG measures brain's electrical activities by using electrodes placed on the scalp, and its major merits include non-invasiveness and easy-accessibility. Besides, physiological studies have discovered that various EEG signal patterns can be used for BCI, for example, slow cortical potentials [2], evoke related potentials [3] and motor imagery signals [4].

This paper focuses on the processing of motor imagery signals. During motor imagery, dynamics of brain oscillations may show interesting patterns, especially in the μ and the β bands ([5], [4]). For example, one may observe an attenuation (termed event-related de-synchronization, or ERD) of the μ and the β bands in the EEG signals over sensorimotor cortices, followed by an enhancement of the bands (termed event-related synchronization, or ERS).

It is argued that individual motor imagery trials do not always follow the ERD/ERS patterns [6]. And they indeed often exhibit rather complex patterns, because the performance of imaginary movement invovles sophisticated spatial-temporal-spectral dynamics in the brain. For example, a synchronization of higher frequency components embeded in a desynchronization of lower frequency components can be found on a specific electrode location at the same moment of time [7]. The understanding of such complex patterns, as well as an appropriate signal processing method to capture the important structures of the patterns, should be crucial to the recognition of motor imagery signals.

However, conventional methods usually focus on space-time dynamics in fixed spectral windows. For instance, our previous work [8] applied empirically selected band-pass filters on the EEG signals, while the complex joint space-time-frequency dynamics and the underlying mechanisms are not yet clearly understood or explored.

This work is our first endeavour to address this issue. Instead of doing band-pass filtering as in conventional methods, we try to explore important EEG features directly in time-frequency domain by using advanced signal processing technologies. In particular, we apply wavelet packets as a time-frequency analysis tool and employ spare component analysis (SCA) [9] to recover sparse source components in the wavelet packets domain. Furthermore we use multiclass common spatial pattern (CSP) filters ([10], [11]) to explore the space-frequency features that are of interest for discrimination. To further enhance the system, we introduce a Bayesian method that combines multiple support vector machines (SVMs) and allows us to incorporate other features like those from [8].

The paper is organized as follows. Section II illustrates the system scheme. Section III describes the feature extraction. Section IV introduces the classification machine. The analysis results on a public available dataset are illustrated in Section V, followed by discussions in Section VI.

II. SYSTEM OVERVIEW

The system is illustrated in Figure 1. There are two sub-systems for feature extraction. We focus on the first one while the second sub-system employs an existing approach which uses direct CSP on filtered signals (for details please see [8]). In the first one, raw signals are transformed into time-frequency domain by using wavelet packet decomposition. The signals are then processed with sparse component analysis to

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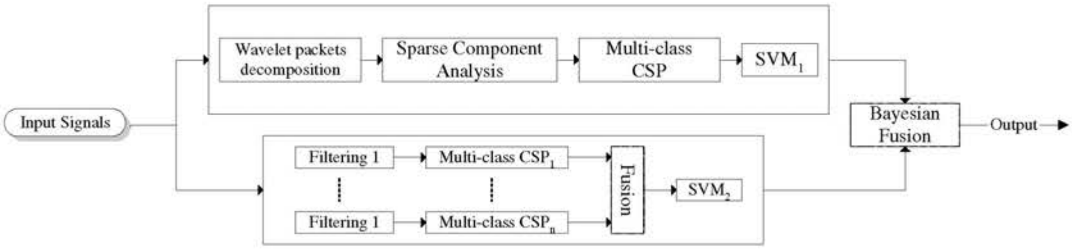

Fig. 1. System Flowchart

recover source signals that are probably associated with motor imagery. A multi-class CSP filter is then applied to exploit most discriminative information in the recovered sources. The features from the two sub-systems are processed with two sets of SVMs, respectively. And the final decision is made with a Bayesian fusion of the outputs of all SVMs.

III. Feature Extraction

A. *Sparse Component Analysis with Wavelet Packet Decomposition*

We assume that EEG signals can be viewed as a linear mixture of m source signals:

$$\mathbf{X} = \mathbf{AS} \tag{1}$$

where $\mathbf{X} = [\mathbf{x}_1 \ldots \mathbf{x}_n]^T$ are the acquired n-channel m-sample EEG signals. The matrix A is an $n \times m$ linear mixing operator, and $\mathbf{S} = [\mathbf{s}_1 \ldots \mathbf{s}_m]^T$ is the group of source components.

It is known that independent component analysis (ICA) may be applied to recovering the linearly mixed sources of EEG signals, providing that $m = n$ (i.e. equal numbers of sources and sensors). Indeed recently there has been a surge of using ICA to process EEG for BCIs (e.g. [12]). But if $m \neq n$ and especially when one has more sources than sensors, the sparse component analysis (SCA) may be a better choice than ICA, for example in the case shown in Figure 2, which demonstrates the efficacy of SCA for recovering 10 sources (face images) from only 6 mixture signals (see [9] for details). Besides, earlier work [13] has shown that the sparse factorization approach of SCA can provide an appropriate tool for the processing of EEG signals.

It is known that the sparsity of source comopnents is the key to the success of SCA [9]. Although EEG signals and their source components may not be sparse in time domain, they are usually sufficiently sparse in time-frequency. Thus, we process the EEG signals with a well-established time-frequency analysis tool named wavelet packets.

Wavelet packets are a generalization of orthonormal wavelets with compact support, producing a tree-structured multiband extension. They are well localized in both time and frequency. Let $\tilde{\mathbf{X}}$ be the wavelet packet representation of a EEG signal $\mathbf{X}$ and $\tilde{\mathbf{S}}$ be the source representation accordingly. Since wavelet packets transformation is linear, we have

$$\tilde{\mathbf{X}} = \mathbf{A}\tilde{\mathbf{S}} \tag{2}$$

The matrices $\tilde{\mathbf{S}}$ can be determined with an algorithm introduced in [9]. In practice, to focus on those frequency bands of more interest for motor imagery classification, we can select the wavelet packets in or close to the range of μ and β rythms. Unlike previous work, we do not reconstruct source components $\mathbf{S}$ from $\tilde{\mathbf{S}}$, since we will continue to investigate the signals in the time-frequency domain.

B. *Discriminative Features by CSPs*

In many neural engineering applications, powerful techniques like ICA or blind source separation often require subjective a posteriori analysis in order to visualise neurophysiologically meaningful components in the outputs. In other words, one expert needs to view some examples of recovered source signals and identify which source corresponds to noise or artifacts. However, it is not easily applicable in this work because we work on selected wavelet packets only and the recovered signals are mixed time-frequency signals.

To solve this problem, we resort to exploiting most discriminative information in the recovered time-frequency signals. It shall be stressed that the method is fully automatic and avoids the neccessity of visualization and inspection by experts. It would suppress possibly redundant information (in terms of discrimination between different classes of motor imagery signals) in the data, and maximize the difference between two classes [11].

Let's first consider a binary classification problem. The CSP consists of calculating a matrix W and a diagonal matrix D through joint diagonalization:

$$W\Sigma^{(1)}W^T = D, \qquad W\Sigma^{(2)}W^T = 1 - D \tag{3}$$

where $\Sigma^{(1)}$ and $\Sigma^{(1)}$ are normalized covariance matrices of the two classes. The normalization is done by dividing the covariance matrix by the trace of the matrix. The diagonal elements of D are sorted in decreasing order.

To extend a binary CSP to multi-class cases, we use a one-against-rest strategy. Simply speaking, for each class ω_k we obtain a particular projection matrix W_k that jointly diagonalizes the covariances of class k and the virtual class

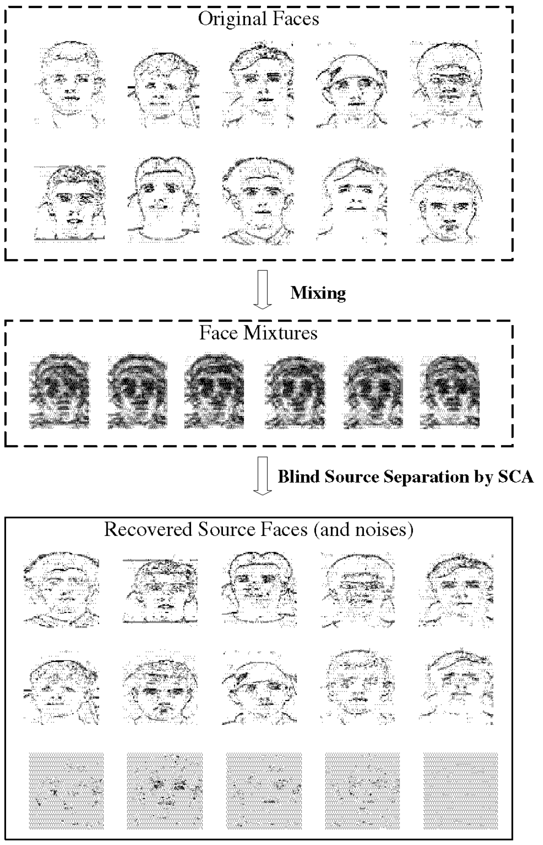

Fig. 2. Blind Source Separation with SCA: An example. In the top box we show six images of linear mixtures of faces. In the bottom we show the recovered faces in addition to five noise images.

containning all the other classes. Since the first j and the last j rows a W_k would yield most discriminative information, we select them from each W_k : $k = 1 \ldots c$ to form a single projection matrix W_g for all class-pairs. Thus W_g would be an $8j$-row matrix in four-class cases. Note that this strategy has been suggested in [14] as one of the best strategies of extending binary CSP to multiclass cases.

Let $\tilde{\mathbf{X}}$ be the recovered source components in the time-frequency domain. We extract the CSP features by calculating the sum energy over time by

$$\mathbf{Z} = \text{diag}\left[(W_g\tilde{\mathbf{X}})(W_g\tilde{\mathbf{X}})^T\right] \tag{4}$$

IV. Classification by Combining SVMs

Upon obtaining EEG features in form of vector $\mathbf{z}$ (the concatenation of $\mathbf{Z}$), the system would process the features with a set of SVMs. In the field of BCI, the capability of SVMs has been successfully demonstrated in a great deal of work such as [15]. And it is known that one advantage of SVMs over conventional neural networks is in its ability to achieve good generalization performance.

In a binary classification case, the output of a SVM takes the following form

$$f(\mathbf{z}) = \sum_{i=1}^{N} \alpha_i y_i \mathbf{k}(\mathbf{z}, \mathbf{z}_i) + \beta_0 \tag{5}$$

where $\mathbf{k}$ is a kernel function on the input pattern $\mathbf{z}$ and a training sample $\mathbf{z}_i$.

To apply SVMs to multiclass cases, we adopt a pairwise mechanism by constructing a SVM for each pair of classes. So there would be six networks for four classes. In addition to the features $\{\mathbf{z}\}$ (a feature vector from $\mathbf{Z}$ by concatenation) obtained in the previous section, we also introduce a feature set $\hat{\mathbf{z}}$ by applying CSP direct on filtered raw EEG signals (see [8]). We deal with the two feature sets with two sets of support vector machines respectively. In other worlds, we have two groups networks referred to as SVM1 and SVM2. The outputs of SVM1 and SVM2 are indicated by $\{y_l : y_l = f_l(\mathbf{z})\}_{l=1:6}$ and $\{\hat{y}_l : \hat{y}_l = \hat{f}_l(\hat{\mathbf{z}})\}_{l=1:6}$ respectively, where l denotes the l-th class-pair.

It is an interesting yet challenging task to effectively combine the classifiers to reach a classifier with better performance. The philosophy behind combining classifiers is, as Kittler et al. put it [16], different classifier designs potentially offer complementary information about the patterns of interest.

Here we present a Bayesian approach to the combination of classifiers. The first step is to interpret the networks' outputs in terms of a posteriori probabilities, e.g. $P(\omega_{k_0}|y_{k_0k_1}, \omega_{k_0} \cup \omega_{k_1})$, where $y_{k_0k_1}$ is the output of the SVM for the class pair $\{\omega_{k_0}, \omega_{k_1}\}$. This can be done with a sigmoid model of the probability function that has been suggested in [17].

$$P(\omega_{k_0}|y_{k_0k_1}, \omega_{k_0} \cup \omega_{k_1}) = \frac{1}{1 + \exp(Ay + B)} \tag{6}$$

Here the parameters A and B are to be learnt empirically and to be fine tuned to achieve best recognition accuracy. Note it is similar with the case of $P(\omega_{k_0}|\hat{y}_{k_0k_1}, \omega_{k_0} \cup \omega_{k_1})$.

Suppose that each class has equal a priori probability. From Bayesian theory, we can derive the following approximation to the probability that an input pattern $\mathbf{x}$ belongs to class ω_k given feature $\mathbf{y}$ (the ensemble of $y_{k_0k_1}$)

$$P(\omega_k|\mathbf{y}) \propto \sum_{k_1=1, k_1 \neq k}^{C} P(\omega_k|y_{kk_1}, \omega_k \cup \omega_{k_1}) \tag{7}$$

And $P(\omega_k|\hat{\mathbf{y}})$ takes a similar form. The total a posteriori probability can therefore be approximated by

$$P(\omega_k|\mathbf{X}) \propto P(\omega_k|\mathbf{y})P(\omega_k|\hat{\mathbf{y}}) \tag{8}$$

We do the final classification by picking out the class ω_k which has the maximal probability $P(\omega_k|\mathbf{X})$.

	k3b	k6b	l1b
Method[8]	12.33 ± 6.60	15.88 ± 8.49	15.67 ± 5.04
This method	8.70 ± 5.04	14.56±9.25	13.70±9.75
Relative Err. Reduction	29.44%	8.33%	12.59%

TABLE I

STATISTICS OF CLASSIFICATION ERROR RATE.

(Average and standard deviation are shown here.)

V. EVALUATION PROCEDURE

We have examined the presented scheme with a publicly available data set from the third International BCI Competition [18]. The data set named IIIa was provided by the Laboratory of Brain-Computer Interfaces (BCI-Lab), Graz University of Technology, Austria. The recording of the data consists of 60 channels out of an EEG amplifier sampling at 250Hz. The data set includes three subjects named 'k3b', 'k6b' and 'l1b'. On each subject, the data consist of 60 trials for each of the four classes (motor imagery of left hand, right hand, foot, tongue). The training set contains 45/30/30 trials per class respectively for the three subjects. The motor imagery is cued: at t=2s from the begin of a trial the system produces an acoustic indication; and from t=3s to 4s it displays an arrow to denote the desired imaginary movement.

In order to obtain an accurate evaluation of the system performance, we ran eight runs of 5-fold cross-validation on the training set. And each run used a particular random partition to create the five folds. In the test, we downsampled the original signals from 125Hz to 64Hz in order to reduce data size and computation cost as well. We performed 4-level wavelet packet docomposition using wavelet function 'db3'. All the parameters of the system were set by empirical optimization, including the kernel type for SVMs, the number of CSP projection vectors, etc.

VI. RESULTS

Table I summarizes the evaluation results in terms of classification error rate, where the presented method is compared with the winner method in the BCI competition ([8]). It can be seen that our method is able to accurately classify the motor imagery signals, by approximately 88% in average. Furthermore, compared with the winner method in competition, our method reduced the error rates significantly – by 29.44%, 8.33% and 12.59% respectively for the three subjects (average 16.79% error reduction).

VII. CONCLUSION

In summary, in this work we have developed an effective approach to multiclass motor imagery classification. The method that combines SCA and CSP in wavelet packet domain is able to extract important space-time-frequency features for classification. And it has been demonstrated that the Bayesian method by combining multiple SVMs can furture boost the performance of the Brain-computer interface in terms of accuracy.

There are a few possible extensions of the method, especially in aspect of advanced modeling of dynamic features in space-time-frequency domain. For example, we may incorporate some variant of hidden Markov models that may help interpret the dynamics of EEG signals from a statistical viewpoint. Besides, it is also promising to introduce certain constraint to the sparse component analysis so as to reflect neurophysiological prior knowledge of the EEG sources.

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