Performance Increase by using a EEG Sparse Representation based Classification Method

Younghak Shin, Seungchan Lee, Soogil Woo and Heung-No Lee*
School of Information and Communications
Gwangju Institute of Science and Technology
Gwangju, Republic of Korea
{shinyh, seungchan, woo, heungno}@gist.ac.kr

***Abstract*— Attempts are being made to make brain-computer interface system (BCIs) commercially viable for normal person. Stable performance is essential so that BCIs could widely be used for general public. We propose a new classification method based on sparse representation of EEG signals and L1 minimization. The proposed method use the common spatial filtering (CSP) and band power feature for classification. We compare the classification accuracy of proposed method to that of the conventional linear discriminant analysis (LDA) method. Our method shows improved accuracy over the LDA classification method regardless of the number of CSP filters.**

Keywords- Electroencephalogram (EEG), Brain-Computer Interface (BCI), Sparse Representation, Compressed Sensing (CS), Common Spatial Pattern (CSP).

I. INTRODUCTION

Brain-computer interface system (BCIs) provides a new communication and control channel between human brain and an external device without any muscle movements [1]. In the past, BCIs have been developed mostly to provide alternative communication means to people who have severe motor disabilities [2]. These days there are some companies applying electroencephalogram (EEG) based BCIs to normal person by using headset shaped scalp electrodes, such as Emotiv EPOC [3] and MindWave [4]. For these commercial BCIs going beyond laboratory researches, important issue is stable performance, *viz*. classification accuracy.

In this paper we propose a *sparse representation* based classification (SRC) scheme for the purpose of increasing the classification accuracy of EEG based BCIs. This SRC method has been used in the face recognition field [5]. The SRC method works by finding a sparse representation of the test signal in terms of a set of training signals inside a dictionary. This sparse representation is efficiently done by using an L1 minimization which is motivated from the compressive sensing (CS) theory [6]. The dictionary design is the critical step for this method. We use band power as a feature, and common spatial pattern (CSP) filtering for making the EEG signals distinguishable for different classes [7].

II. METHODS

A. Experimental data

In this study, we use a BCI Competition III data set (Data set IVa) [8] which were recorded from five subjects. Subjects have taken the same procedure of a BCI experiment in which there are two classes, Right hand, and Right foot of motor imagery movements. The data recording was made using BrainAmp amplifiers and a 128 channel Ag/AgCl electrode cap from ECI. 118 EEG channels were measured at positions of the extended international 10/20-system. Signals were band-pass filtered between 0.05 and 200Hz and then digitized at 1000Hz. For off line analysis signals were downsampled to 100Hz.

B. Data analysis

We take a data segmentation for following analysis. We use 1000~2000ms of signal samples (100 samples) after the Cue has been presented. Next, to eliminate the noise that is not related with sensorimotor rhythms (SMRs), we use a band-pass filter with 8~15Hz cut off frequency.

To reduce the dimension of feature vector and make distinguishable features, we use the CSP filtering. CSP is a powerful signal processing technique that has been successfully applied for EEG-based BCIs [7].

Let $\mathbf{X} \in \mathbb{R}^{C\times T}$ be a segment of EEG signals where C is the number of EEG channels. In this study, C is 118, and T is the number of sampled time points collected in all the trials. We use 100 samples (one second). We have two classes of EEG training trials $\mathbf{X}_R \in \mathbb{R}^{C\times T}$ and $\mathbf{X}_F \in \mathbb{R}^{C\times T}$ each corresponding to the Right hand '*R*' and Foot '*F*' movement. Using the CSP method, we obtain the CSP filters $\mathbf{W} \in \mathbb{R}^{C\times C}$. We call each column vector $\mathbf{w}_i \in \mathbb{R}^{C} (i = 1, 2, ..., C)$ of $\mathbf{W}$ a spatial filter. Among them, we use n CSP filters from the front and another set from the back. Then, we can make this as the CSP filtering matrix $\overline{\mathbf{W}} \in \mathbb{R}^{C\times 2n}$, i.e., $\overline{\mathbf{W}} := [\mathbf{w}_1, ..., \mathbf{w}_n, \mathbf{w}_{C-n+1}, \mathbf{w}_C]$. Given the two classes of EEG training signals, we define the CSP filtered signals, i.e.,

$$\overline{\mathbf{X}}_R \in \mathbb{R}^{2n\times T} := \overline{\mathbf{W}}^{\mathrm{T}}\mathbf{X}_R$$
$$\overline{\mathbf{X}}_F \in \mathbb{R}^{2n\times T} := \overline{\mathbf{W}}^{\mathrm{T}}\mathbf{X}_F \tag{1}$$

Next, we compute band power of each class signal. In this study, the power of the CSP filtered signal, i.e., the second moment of each row of $\overline{\mathbf{X}}_R$ and $\overline{\mathbf{X}}_F$ is the band power from 8 to 15 Hz.

C. Linear Sparse Representation Model

In this section, we aim to introduce the sparse representation of the test signal. Let N_t be the number of total training signals for each class $i = R, F$. We define the dictionary matrix $\mathbf{A}_i = [\mathbf{a}_{i,1}, \mathbf{a}_{i,2}, ..., \mathbf{a}_{i,N_t}]$ for $i = R, F$ where each column vector $\mathbf{a} \in \mathbb{R}^{m\times 1}$ having dimension $m = 2n$ is obtained by concatenating the $2n$ band power features. The same procedure is repeated for the right hand and right foot classes. By combining the two matrices, we form the complete dictionary, $\mathbf{A} := [\mathbf{A}_R; \mathbf{A}_F]$. Thus, the dimension of $\mathbf{A}$ is $m \times 2N_t$.

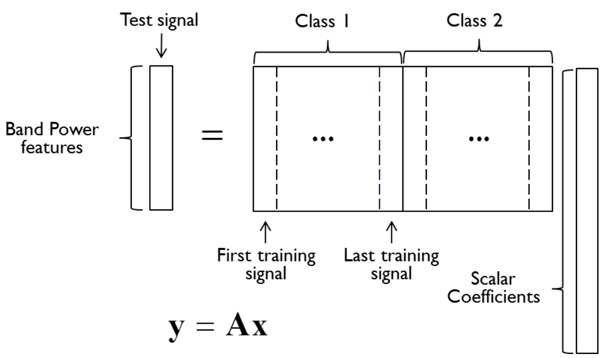


Figure 1. Design a dictionary and linear sparse representation model

Figure 1 shows the proposed model. We apply the same procedure done to obtain the columns of the dictionary to the test signal. Thus, the dimension of $\mathbf{y}$ is the same as the dimension of the columns of the dictionary $\mathbf{A}$. Then, this test signal $\mathbf{y}$ can be sparsely represented as a linear combination of some columns of $\mathbf{A}$:

$$\mathbf{y} = \sum_{i=R,F} x_{i,1}\mathbf{a}_{i,1} + x_{i,2}\mathbf{a}_{i,2} + \cdots + x_{i,n_t}\mathbf{a}_{i,N_t} \tag{2}$$

where $x_{i,j} \in \mathbb{R}, j = 1, 2, ..., N_t$ are scalar coefficients. Then, we can represent this as a matrix algebraic form:

$$\mathbf{y} = \mathbf{A}\mathbf{x} \tag{3}$$

where $\mathbf{x} = [x_{R,1}, x_{R,2}, ..., x_{R,N_t} x_{F,1}, x_{F,2}, ..., x_{F,N_t}]^T \in \mathbb{R}^{2\cdot N_t}$. For example, we expect that the test signal $\mathbf{y}$ of class R can be represented as the training signals of class R.

$$\mathbf{y}_R = \mathbf{A}\mathbf{x}_R \in \mathbb{R}^{m\times 1} \tag{4}$$

where $\mathbf{x}_R = [\mathbf{a}_{R,1}, \mathbf{a}_{R,2}, ..., \mathbf{a}_{R,N_t}, 0, ..., 0]^T \in \mathbb{R}^{2N_t}$ is a coefficient vector whose elements are zero except some elements associated with test signals of class R. Sparse representation of the test signal $\mathbf{y}$ can be made when the number of non-zero coefficients of $\mathbf{x}$ is much smaller than N_t.

D. Sparse Representation by L1 Minimization

We have the number of total training signals $2N_t$ which is larger than the number of CSP filters $(m = 2n)$. Thus, the linear equation (4) is under-determined $(m < 2N_t)$. Recent studies in the Compressed Sensing theory have shown that the L1 norm minimization, given below, can solve this under-determined system well in polynomial time [9]:

$$\min \|\mathbf{x}\|_1 \text{ subject to } \mathbf{y} = \mathbf{A}\mathbf{x} \tag{5}$$

There are many L1 minimization algorithms. In this paper, we use one of the standard linear programming methods [10], the 'SolveBP' function implements the basis pursuit algorithm available in the SparseLab, which is a free MATLAB software package [11].

E. Sparse Respresentation based Classification

After solving the L1 minimization problem, the nonzero elements of $\mathbf{x}$ must be corresponding to the column of class i. Because the EEG signals are very noisy and non-stationary, the nonzero elements may appear in the indices corresponding to the column of another class. To make use of the sparse representation result, the coefficient vector $\mathbf{x}$, in a classification problem, we introduce the characteristic function δ [5]. For each class i, we define its characteristic function $\delta_i : \mathbb{R}^{2N_t} \to \mathbb{R}^{2N_t}$ which selects the coefficients associated with class i. For $\mathbf{x} \in \mathbb{R}^{2N_t}$, $\delta_i(\mathbf{x}) \in \mathbb{R}^{2N_t}$ is a new vector which is obtained by nulling all the elements of $\mathbf{x}$ that are associated with the other class. Then we can obtain the residuals $r_i(\mathbf{y}) := \|\mathbf{y} - \mathbf{A}\delta_i(\mathbf{x})\|_2$ for L and R. Then, the classification rule is given by:

$$\text{class}(\mathbf{y}) = \arg\min_i r_i(\mathbf{y}) \tag{6}$$

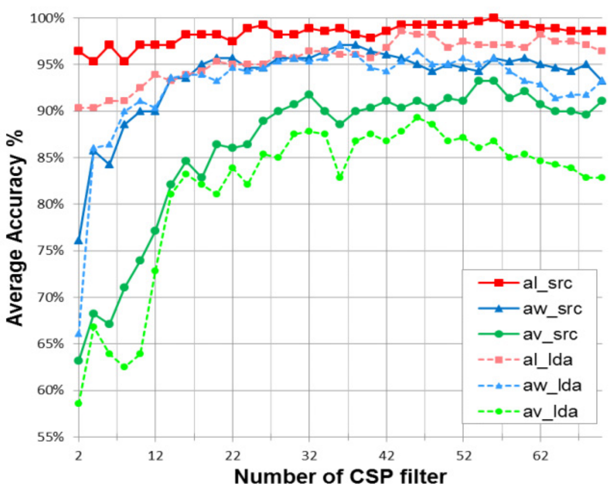
Thus, we determine the class i that has the minimum residuals.

III. Results

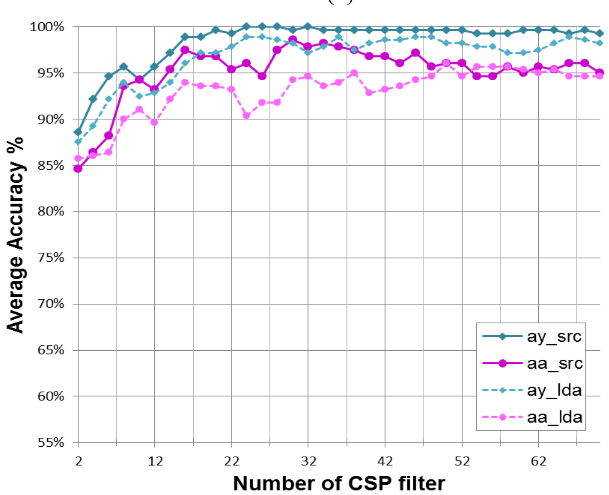
We have analyzed five data sets using proposed SRC method and conventional linear discriminant analysis (LDA) method. To evaluate the average classification accuracy using limited size datasets, we use the statistical leave-one-out (LOO) cross-validation method with the same total number of data trials for each subject [12]. The classification accuracy is calculated from the following equation:

$$\text{Accuracy}(\%) = \frac{\text{correct test trials}}{\text{total test trials}} \times 100 \qquad (7)$$

Figure 2 shows the classification accuracy (%) of SRC and LDA as a function of the number of CSP filters for each subject. Figure 2 (a) shows the results of subject al, aw and av. Solid line represents the SRC accuracy and dashed line represents the LDA accuracy. Figure 2 (b) shows the results of subject ay and aa. For each selection on the number of CSP filters, SRC performs better than LDA does with few exceptions. Thus, it can be said that SRC has better classification accuracy than LDA regardless of the number of CSP filters in Figure 2. To investigate the statistical significance of the observed accuracies in Figure 10, we performed a paired *t*-test for each subject. The obtained *p*-value of the *t*-test was less than 0.05 for all subjects, which indicates that the difference was significant.



(a)



(b)

Figure 2. Classification accuracy (%) per subject with different number of CSP filters. (a) Classification accuracies for subject al, aw and av. Solid line represents SRC results and dashed line represents LDA results. (b) Classification accuracies for subject ay and aa.

IV. Conclusions

We apply the idea of sparse representation as a new classification method for the motor imagery EEG based BCIs. The sparse representation method needs a well-designed dictionary matrix made of a given set of training data. We use the CSP filtering and the band power to produce the columns of the dictionary matrix. We have shown that a good classification result can be obtained by the proposed method. In addition, we have compared with the conventional approach, *viz.*, the LDA method, which is well known for robust classification performance. Our method shows improved accuracy over the LDA classification method regardless of the number of CSP filters.

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