A Framework of Adaptive Brain Computer Interfaces

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Abstract

Non-stationarity is often found in session-to-session transfers of Brain Computer Interfaces (BCIs). To cope with the problem, a framework based on Common Spatial Patterns (CSP), Linear Discriminant Analysis (LDA), and covariate shift adaptation methods is proposed. Covariate shift adaptation is an effective method which can adapt to the testing sessions without the need for labeling the testing session data.

This framework has been applied on one electrocorticogram (ECoG) dataset and one Electroencephalogram (EEG) dataset from BCI Competition III. Despite the different characteristics of ECoG and EEG, non-stationarity appeared in both datasets. Results showed that the proposed framework compares favorably with those methods used in the BCI Competition, revealing the effectiveness of covariate shift adaptation in tackling the non-stationarity in Brain Computer Interfaces.

Index Terms—-covariate shift, adaptive brain-computer interface, ECoG, EEG

1. Introduction

Brain Computer Interface (BCI) can be implemented with non-invasive or invasive methods. EEG-based BCI, a traditional and non-invasive practice, records the brain activities over the scalp and recognizes the activated cortical area corresponding to the imagined task, for example, motor imagery. Alternatively ECoG, which is intracranial but not intracortical, can be utilized for such an interface. Compared with ECoG, EEG is safer and easier to be accessed; whereas ECoG offers signals with higher signal-to-noise ratio, amplitude, spatial resolution and wider signal bandwidth [20]. However, one widely known shortcoming of EEG is non-stationarity, which may be caused by the user, user fatigue, and small differences in electrode position [2]. Non-stationarity often manifests itself most obviously in session-to-session transfers, causing changes of EEG feature distributions from one session to another. This illustrates the non-stationary nature of the BCI signal and provides a rationale for the design of an adaptive BCI system [3]. As for ECoG, though electrode positions are fixed and relatively stable impedance can be ensured, the attention level of user is hard to be maintained at the same level. Moreover, the accessibilities of ECoG data are often restricted to patients with epilepsy, thus non-stationarity would be inevitable due to intermittent occurrences of epileptic spikes. Although there are fewer researches concerning the adaptive ECoG-based BCIs, several studies have been conducted on adaptive EEG-based BCI systems with positive results. Among the adaptive EEG-based BCIs, Vidaurre et al. adopted an online updated classifier by adaptive estimation of the information matrix (ADIM) [4], [5]. Blumberg et al. developed Adaptive Linear Discriminant Analysis, updating mean values and covariances continuously in time for different motor imaginary tasks [6]. However, most of the adaptive methods are based on supervised learning techniques (e.g., [2], [4], [5]), which need labeled test samples and are, thus, costly. Covariate shift adaptation is a method which can overcome this shortcoming, assuming that the input distributions of training and testing sessions are different while the conditional distribution of output given input remains unchanged [12].

To test the effectiveness of covariate shift adaptation method, one ECoG dataset and one EEG dataset from BCI Competition III were chosen and analyzed, both of which were quite challenging in coping with non-stationarity in session-to-session transfers. In the test, a framework based on Common Spatial Patterns (CSP), Linear Discriminant Analysis (LDA) and covariate shift adaptation was applied. In this paper the introduction of datasets and covariate shift adaptation methods are presented first, followed by results and discussions.

2. Datasets

2.1. Dataset I from BCI Competition III

BCI Competition III dataset I [15] was demanding and challenging in the aspect of session-to-session transfers. Cue-based ECoG motor imagery data were recorded from the same subject on two different days with about 1 week in between. A 8x8 ECoG platinum electrode grid (size approximately 8x8 cm) was placed on the contralateral (right) motor cortex and the imaginary movements were about tongue and left small finger separately. The first session which contains 278 trials were given for training while 100 trials in the second session needed to be classified. All recordings were performed with a sampling rate of 1000Hz. Every trial consisted of either an imagined tongue or an imagined finger movement and was recorded for 3 seconds duration. To avoid visually evoked potentials being reflected by the data, the recording intervals started 0.5 seconds after the visual cue had ended.
The competition winner combined three features and utilized linear SVM as the classifier [16] with the classification accuracy as high as 91%.

2.2. Dataset IVc from BCI Competition III

Dataset IVc [17] was recorded from one healthy subject. Visual cues indicated for 3.5 seconds which of the following 3 motor imageries the subject should perform: left hand, right foot and tongue. Only 210 trials labels of respectively left hand and right hand were given for training. 420 test trials were recorded 4 hours after the training sessions. The testing sessions were similar to the training sessions, but the motor imagery had to be performed for 1 second only, compared to 3.5 seconds in the training sessions. The other difference was that the class tongue was replaced by the class relax.
118 EEG channels were measured at positions of the extended international 10-20 system. Signals were band-pass filtered from 0.05 to 200 Hz and then digitized at 1000 Hz with a 16 bit (0.1 uV) accuracy. The data version downsampled to 100 Hz was used for analysis.The evaluation criterion was Mean Square Error (MSE). The competition winner applied CSP and LDA, and MSE was in the end reduced at 0.30 after standardization of the output.

3. Methods

3.1. Feature Extraction by CSP and the Baseline Classifier LDA

Common Spatial Patterns (CSP) is one of the most popular spatial filters of multi-channel EEG-based BCIs in recent years. In contrast to other spatial filters, CSP generates features ready to be fed into the classifier. After band-pass filtering the EEG signals in the frequency range of interest, high or low signal variance reflects strong or attenuated rhythmic activity, respectively [7]. When classifying EEG into two tasks, CSP maximizes the variance of one class while minimizing the variance of the other and, thus, reflects the task specific activation patterns.
Linear Discriminant Analysis (LDA) is also a popular classification method in BCI applications [9]. LDA can be realized by the linear least-squares method if the target labels $\{y_i\}_{i=1}^N$ corresponding to the feature vectors $\{x_i\}_{i=1}^N$ for class C_1 are set to be $1/N_1$ and the target labels of class C_2 are set to $-1/N_2$, where N_1 and N_2 are numbers of samples of classes C_1 and C_2, respectively. More specifically, for a linear model

$$\hat{f}(x;\theta) = \theta_0 + \sum_{i=1}^{d} \theta_i x^{(i)}, \tag{1}$$

where $x^{(i)}$ is the ith element of an d-dimensional feature vector x, the parameters are learned by the least-squares method:

$$\min_{\theta} \sum_{i=1}^{N} \left(y_i - \hat{f}(x_i;\theta) \right)^2. \tag{2}$$

The solution is given as

$$\hat{\theta}_{LDA} = (X^T X)^{-1} X^T y, \tag{3}$$

where

$$X \equiv \begin{pmatrix} 1 & x_1^T \\ 1 & x_2^T \\ \vdots & \vdots \\ 1 & x_N^T \end{pmatrix}, \tag{4}$$

$y = (y_1, y_2, ..., y_N)$, and X^T denotes the transpose of X.

3.2. Covariate Shift Adaptation by IWLDA

Covariate shift is defined as the situation where the training input points and test input points follow different distributions, while the conditional distribution of output values given input points is unchanged [12].A prime example of covariate shift in EEG-based BCIs occurs when, given different experimental sessions of the same imaginary tasks, event-related synchronization/desynchronization cortical distributions remain unchanged, but the means and variances shift in the feature distribution for each task.
Under covariate shift, ordinary Linear Discriminant Analysis (LDA) is not consistent [12], [19], i.e., even when infinitely many training samples are provided, one cannot obtain the optimal solution. To cope with this problem, Importance Weighted Linear Discriminant Analysis (IWLDA) was proposed [11], [12].

IWLDA is an extension of LDA based on the concept of *importance sampling*. The importance is defined as the ratio of test and training input densities:

$$w(x) = \frac{p_{te}(x)}{p_{tr}(x)}. \tag{5}$$

After the introduction of the importance and a regularizer, the parameters are learned as

$$\min_{\theta} \sum_{i=1}^{N} w(x_i) \left(y_i - \hat{f}(x_i; \theta) \right)^2 + \lambda \|\theta\|^2, \tag{6}$$

where $\lambda\ (\geq 0)$ is the regularization parameter. The IWLDA solution is given by

$$\hat{\theta}_{IWLDA} = (X^T D X + \lambda I)^{-1} X^T D y, \tag{7}$$

where D is the diagonal matrix with the i-th diagonal element $D_{i,i} = w(x_i)$ and I is the identity matrix [11]. λ can be determined by cross-validation, see details in [12]. IWLDA is proved to be consistent even in the presence of covariate shift.

3.3. Direct Importance Estimation

A naive approach to importance estimation would be to first estimate the training and testing densities separately from training and testing input samples, then estimate the importance by taking the ratio of the estimated densities. However, density estimation is known to be a difficult problem, particularly in high-dimensional cases. Therefore, this naive approach may not be effective; directly estimating the importance without estimating the densities would be more promising [11].
There are two ways to directly estimate the importance, namely Kullback-Leibler Importance Estimation Procedure (KLIEP) and Unconstrained Least-Squares Importance Fitting (uLSIF). The former is based on the minimization of Kullback-Leibler divergence while the latter estimates the importance by the least-squares approach, and the details could be referred to [11] and [13]. The classifiers realized with KLIEP and uLSIF are named IWLDA1 and IWLDA2.

4. Results

4.1. Adaptation Test on BCI Competition III Dataset I

There is no broad consensus about what type of features should be extracted for ECoG based BCIs. In [21] smoothed Movement-related Cortical Potential (sMCP) was considered the most informative feature; while [22] claimed that AR coefficients are discernible enough to be classified; and [23] sought the sum of power of ECoG voltage filtered in four subbands ranging from $1-60$ Hz to $300-6000$ Hz, in order to reduce the influence of strong assumptions. Also the analysis of this dataset led to several journal as well as proceeding papers [24]–[28], which involved different strategies.
At the beginning we plotted the log-log spectrums, channel by channel. The scaled spectrum followed 1/f noise shape, and all the channels displayed a sharp spike at 50 Hz which should be attributed to the working frequency interference [29], while a few of them demonstrated the discernible pattern below 50Hz (see figure 1). In [25] frequency spectrum below 45 Hz of each channel was examined, and the author chose some channels with separable spectrum characteristics, calling them 'good channels'. However, what concerns us most is the frequency range, since we decided to apply CSP and LDA. Thus in the same way spectrum below 50 Hz of each channel was examined and special attention was paid to the separable frequency range in so-called 'good channels'(see figure 2). Finally the frequency of interest was determined from 8 to 30 Hz.

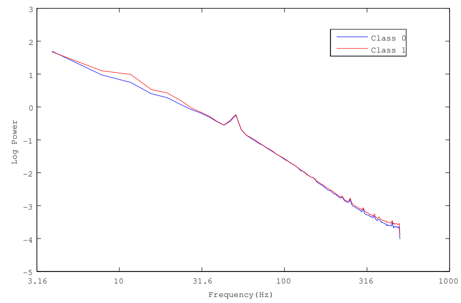

Figure 1: The log-log psd followed 1/f noise shape, with working frequency interference

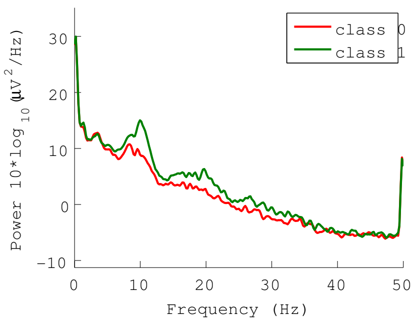

Figure 2: A 'good' channel, with the discernible frequency range from 8 to 30 Hz

The shift of features can be illustrated by figure 3, in which the separation hyperplane for the training session was represented by the blue line. From the figure it is not difficult to see that the features did shift between two sessions, yet most of the testing trials can be classified by the original separation hyperplane. We tested with LDA, IWLDA1, and IWLDA2 on this dataset for several times. For the feature dimension from 2 to 6, the results are listed in table1, and it is clear that for different feature dimensions, IWLDA is good at improving the classification accuracy. To understand how IWLDA worked, the separation hyperplane for feature dimension 2 by IWLDA1 was illustrated by the magenta line in the figure. Although the labels of test trials were not given, the separation hyperplane was rotated a little, resulting in a better classification.

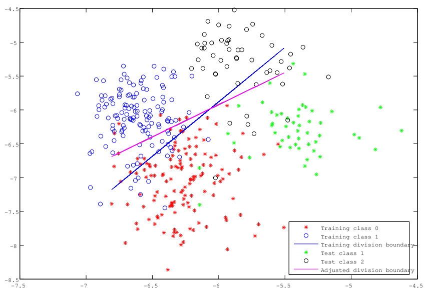

Figure 3: Shift of features between training and testing sessions, BCI Competition III Dataset I

Table 1: Testing results with different feature dimensions

feature dimension	LDA	IWLDA1	IWLDA2
2	0.84	0.91	$0.84 \sim 0.91$
4	0.89	$0.91 \sim 0.92$	$0.90 \sim 0.92$
6	0.84	$0.83 \sim 0.88$	$0.88 \sim 0.89$

4.2. Experimental Results on BCI Competition III Dataset IVc

It is clearly shown in many previous studies, filtering must precede CSP in order to make CSP optimal for the separation of two classes. By plotting the spectrum of all channels (see figure 4) using EEGLAB [18], it can be observed that the alpha rhythm is more obvious than the beta rhythm. Moreover, alpha band is more discernible in many channels, as shown in figure 5. Thus we decided to apply alpha band-filtering only although the competition winner extracted features from both alpha and beta bands.

After alpha band filtering, the different distributions of training and testing sets were verified by plotting the features extracted by CSP for left hand and right foot imaginary movements, as shown in figure 6 that there was a need to shift the classification boundary. Note only two dimensions of features which contained maximum information were drawn for the ease of visualization. However, for this dataset the optimal feature dimension was 6, so it was not possible to represent the adjusted boundary in figure 6.

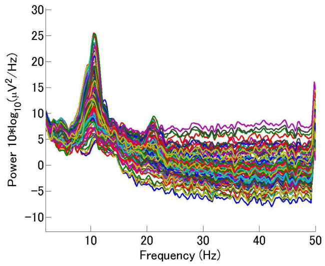

Figure 4: Spectrum for 118 channels, right foot imaginary task

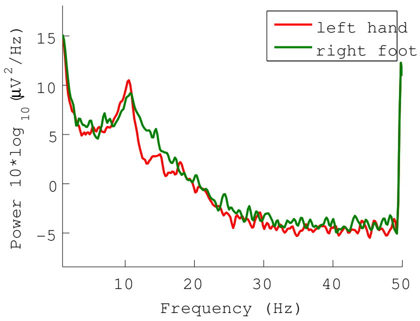

Figure 5: Discernible alpha band for one representative channel

Despite the different distributions, the competition winner standardized the outputs to make MSE as small as 0.30. At first we found that MSE could be reduced to $0.26 \sim 0.28$ if the analyzed data length was slightly extended to 1.1s or 1.2s while the IWLDA methods reached $0.24 \sim 0.28$. To focus on the investigation of covariate shift adaptation, only the left hand and right foot imaginary movements were under consideration, the MSE results are shown in table 2. It can be observed that result of IWLDA1 was not stable, and thus we also tried bagged-IWLDA(BIWLDA), which means applying IWLDA on randomly drawn training samples from the whole training set, then repeating the process for many times (in the current study 30 times), getting the outputs averaged. Figure 7 showed the classification results of the two imaginary movements and demonstrated the effectiveness of IWLDA methods.

Table 2: MSEs by LDA (baseline), IWLDA and Bagged IWLDA(BIWLDA)

Method	LDA	IWLDA1	IWLDA2	BIWLDA1	BIWLDA2
MSE	0.22	$0.11 \sim 0.6269$	$0.0991 \sim 0.1117$	0.088	0.11

The results showed that the covariate shift adaptation methods worked very well. Among them, BIWLDA1 was proved to be much more stable than IWLDA1, while

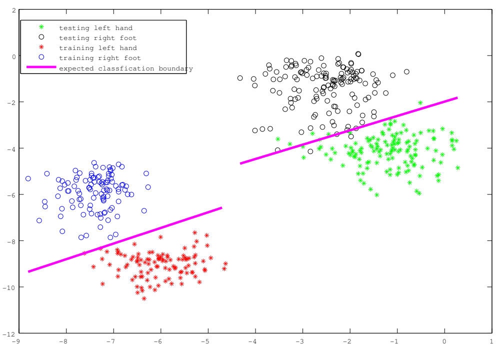

Figure 6: Different feature distributions between training and testing sessions, BCI Competition III Dataset IVc

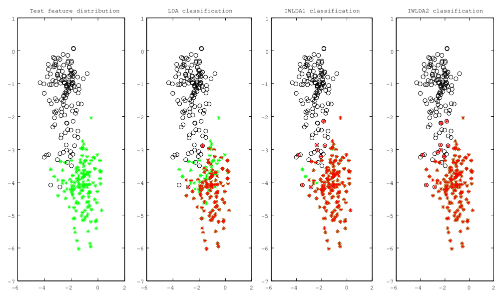

Figure 7: Classification Results of LDA, IWLDA1, and IWLDA2, Before standardization of the outputs, test trials that were classified as left hand were marked red.

IWLDA2 and BIWLDA2 were highly comparable to each other.

5. Discussion

As analyzed above, both EEG dataset and ECoG dataset displayed non-stationarity in BCI applications. The reasons could be due to the fact that the long time interval between training and testing sessions affected the attention level or motivation of the subjects, causing the shift of feature distributions. Shenoy et al. [1] also pointed out in their study that non-stationarity was due to the different background of EEG activities during the online feedback session because visual feedback was introduced. However, this could not be considered a reason in our study since the experiment setup remained the same for both datasets.

In 4.2 and 4.1 we demonstrated the adaptation application on the two datasets. For the EEG dataset, two sessions were recorded on the same day with more than three hours in between, and bagging combined with IWLDA or IWLDA2 performed better than the original LDA method. However, for the ECoG experiment, although two sessions were recorded with a week in between, because of the high signal-to-noise ratio, IWLDA worked well enough in adaptation to the testing session. The explanation could be that bagging usually works in reducing estimation variance: as EEG tends to have high variability, reducing variance is essential to improving the performance; on the other hand, ECoG data samples are much more stable with less variance, which means the reduction of bias by original covariate adaptation would result in a good adaptation.

There are several publications about applications on ECoG Dataset I of the BCI Competition III [24]–[28]. Among them, [25], [27], [28] had reached high classification accuracy of either 92% or 93%, which is highly comparable to the results of the proposed framework. However, there is no introduction of adaptation concepts in these publications, which either put more emphasis on feature selection [27], [28], or resorted to standardizing the features of each trial [25].

6. Conclusions

In the current study, one ECoG dataset and one EEG dataset from BCI Competition III were analyzed and investigated. From the results, we arrive at the following conclusions:

With covariate shift adaptation application, the commonly used CSP combined with LDA become adaptive to ECoG and EEG data in the testing sessions. Considering the effectiveness and relative simplicity of this method, we are able to claim that covariate shift adaptation tackles the non-stationarity in session-to-session transfers, and therefore propose a framework based on Common Spatial Patterns (CSP), Linear Discriminant Analysis (LDA) and covariate shift adaptation techniques, as the framework compares favorably with those methods used in the BCI Competition.

Another conclusion drawn by our study is that when there is a need for shifting and rotating the classification hyperplane, covariate shift adaptation is effective in adaptation, which is in accordance with [1]. Consequently, it is worth considering integrating the covariate shift adaptation techniques into the future BCI, allowing it run at the beginning of every session or every one hour. Also, it would be worth our efforts to test the covariate shift method in a feedback involved scene.

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