Unsupervised Adaptation Based on Fuzzy C-Means for Brain-Computer Interface

Guangquan Liu, Gan Huang, Jianjun Meng, Dingguo Zhang and Xiangyang Zhu
School of Mechanical Engineering, Shanghai Jiao Tong University
Shanghai, 200240, China
Email: guangquanliu@gmail.com

***Abstract*—An important property of brain signals is their nonstationarity. How to adapt a Brain-Computer Interface (BCI) to the changing brain states is one of the challenges faced by BCI researchers, especially in a real application scenario where the subject's real intent is unknown to the system. In this paper, an unsupervised approach based on Fuzzy C-Means (FCM) algorithm is proposed for the online adaptation of the LDA classifier for electroencephalogram (EEG) based BCI. The FCM method and other two existing unsupervised adaptation methods are applied to groups of constructed artificial data with different data properties. The performances of these methods in different situation are analyzed. Compared with the other two unsupervised methods, the proposed method shows a better ability of adapting to changes and discovering class information from unlabelled data. At last, the methods are applied to real EEG data from data set IIb of the BCI Competition IV. Results of the real data agree with the analysis based on the artificial data, which confirms the effectiveness of the proposed method.**

I. Introduction

Brain-computer interfaces (BCIs) are systems that allow their users to communicate with a computer program or control a mechanical device directly by intent rather than by neuromuscular passway [1]. One of the challenges faced by BCI researchers is the nonstationarity of the subject's brain states, reflected as changes in the statistical properties of the electroencephalogram (EEG) signals, which has been widely reported by literature [2]–[4]. Due to the nonstationarity, the BCI system trained on one session may become ill-suited to the succeeding sessions.

In order to improve the adaptability of a BCI system to the changing brain states, various adaptation methods have been investigated. In [5]–[7] the classifier was updated manually after several runs, according to the experimenter's experience and judgement. In [2]–[4], [8]–[10] the classifier was updated automatically by different machine learning methods. Most of these methods need true label information to update the classifier. In other words, these methods are supervised.

However, in a practical application scenario, the real intention of the subject is not always known to the system [2], [11], [12]. Considering this situation, some research groups have paid attention to unsupervised adaptation algorithms. In [12] three types of unsupervised adaptation procedures for linear discriminant analysis (LDA) classifier were proposed and analyzed. A limit of these procedures is that they are based on an assumption that during the online sessions, the vector connecting the two class means keeps nearly constant, which may not always be true in real BCI. Without such assumptions, Gan [13] introduced an incremental adaptation procedure for LDA and Bayesian classifiers, which used the estimated label to guide the updating of the classifier. This "decision-directed" approach may have some potential dangers. If a trial is wrongly classified, the classifier will be misled by it. To avoid these dangers, some non-incremental unsupervised clustering methods have also been reported. In [14], Blumberg proposed an adaptive linear discriminant analysis (ALDA) method for simulated online clustering of EEG patterns. This method is essentially a Gaussian mixture model (GMM) based adaptation method, although not explicitly named. The initial data distributions were estimated from a labelled training period. A limit of this strategy is that, if the feature distribution shifts far away from the training session during long-term use, this initial parameter will not be valid any more.

In this paper, we adopt the Fuzzy C-Means (FCM) algorithm to update the LDA classifier for a simulated online BCI scenario in an unsupervised manner. In order to investigate its performance in different situations, the proposed method is applied to several types of constructed artificial data with different properties, as well as real EEG data from data set IIb of the BCI competition IV. The performance of our method is compared with an incrementally updated LDA and a GMM based adaptive LDA. Our method shows a better performance than the other two methods not only on the artificial data, but also on the real EEG data, which confirms the effectiveness of the proposed method.

II. Methods

A. Feature extraction

Common spatial patterns (CSP) is used as a feature extractor in this paper. The formulae of this algorithm can be seen in [15].

B. LDA classifier

Fisher's LDA is used as a classifier in this paper. If μ_1 and μ_2 are the means of the two classes, and Σ_1 and Σ_2 are the corresponding covariance matrices, then an LDA classifier can be determined by these parameters. The formulae of LDA can be found in [16].

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C. Supervised adaptation of the classifier

We denote the parameter set as $\Theta = \{\mu_1, \mu_2, \Sigma_1, \Sigma_2\}$. Since the LDA classifier can be fully determined by Θ, in order to update the classifier, the main work we need to do is to update Θ.

In a supervised scenario, where all the trials before the current time are provided with a true label, the adaptation work is relatively easier. If x_k is the latest feature vector whose true label is already known, we update Θ in the following way:

$$\mu_i(k) = \mu_i(k-1)(1-UC) + x_k \cdot UC \tag{1}$$

$$\begin{aligned}\Sigma_i(k) &= \Sigma_i(k-1)(1-UC)\\ &+(x_k - \mu_i(k))(x_k - \mu_i(k))^T \cdot UC\end{aligned} \tag{2}$$

where i is the true label of $x(t)$, and UC is the update coefficient.

D. Unsupervised adaptation of the classifier

As mentioned in [4], "in a realistic BCI scenario, the labels of ongoing trials may not always be available". In such a case, the BCI system has to be updated in an unsupervised manner, if adaptation is necessary. Fuzzy C-Means method [17] has been used for many unsupervised clustering problems; however, it has not been applied to the adaptation of BCIs. In this work, we adopt this method for the unsupervised adaptation of an LDA classifier.

1) Fuzzy C-Means: In a clustering problem, fuzzy clustering algorithms partition the feature space into overlapping areas (classes) based on the similarity among feature vectors, and each feature vector is provided with a membership value to each class. However, in this work, FCM is not used directly as a clustering method, but used as a technique for the unsupervised estimation of the parameter set Θ.

FCM is an iterative algorithm, and in each iteration there are two steps.

Step 1: Given the class means, the Euclidean distance between the kth feature vector and the ith class mean can be computed:

$$d_{ik} = \sqrt{(x_k - \mu_i^{(t)})^T (x_k - \mu_i^{(t)})} \tag{3}$$

where t is the iteration index. Then the membership value can be computed as follow:

$$p_{ik} = \frac{1}{\sum_{j=1}^{C} (d_{ik}^2 / d_{jk}^2)^{1/(m-1)}} \tag{4}$$

where m is the fuzziness exponent ($m > 1$), and C is the number of classes (in this work, $C = 2$).

Step 2: Given the membership values, the class means can be updated as follow:

$$\mu_i^{(t+1)} = \frac{\sum_k (p_{ik})^m x_k}{\sum_k (p_{ik})^m} \tag{5}$$

Similarly, the covariance of each class can also be estimated:

$$\Sigma_i = \frac{\sum_k (p_{ik})^m C_{ik}}{\sum_k (p_{ik})^m} \tag{6}$$

where $C_{ik} = (x_k - \mu_i)(x_k - \mu_i)^T$. Since Σ_i is not involved in step 1 of each iteration, it can be computed only once at the last iteration. This not only saves computational time, but also avoids the danger of inappropriate estimation of covariance matrices and membership values in the iteration.

The initial parameter set Θ_{init} is treated as a variational parameter but not a constant one. The current Θ_{init} is estimated based on the historical estimations of Θ. Let $\Theta^{(0)}$ denote the Θ computed from the labelled training session, $\Theta_{init}^{(k)}$ denote the Θ_{init} used for estimation when the kth unlabelled trial come, and $\Theta^{(k)}$ denote the estimated Θ after the kth unlabelled trial. Then we determine $\Theta_{init}^{(k)}$ in the following way:

$$\Theta_{init}^{(k)} = \begin{cases} \Theta^{(0)}, & \text{if } k \le N_{hi}, \\ \frac{1}{N_{hi}} \sum_{j=k-N_{hi}}^{k-1} \Theta^{(j)}, & \text{else} \end{cases} \tag{7}$$

where N_{hi} is the size of the historical set of the estimations. We do not use a constant or random Θ_{init}, in order to avoid the potential danger that the class distribution shifts far away from the initial distribution, or even becomes mirrored to the initial distribution (corresponding to a class label switch) during long-term use.

2) Other existing methods: As references, two existing unsupervised adaptation methods are compared with the FCM method, namely, the incremental updating method [13] and the GMM based method [14].

III. Application

A. Artificial data

In order to investigate the performance of the proposed method and the factors which influence the performance, we construct groups of artificial data. Since these data are artificially constructed, we can control their properties, e.g., separability, type of the nonstationarity, and degree of the nonstationarity. In such a way, we can detailedly investigate how these properties affect the adaptation of a BCI.

As reported in [4], there are mainly two types of change in EEG data, namely, shift in the transition from one session to another, and gradually change in the course of a single session. In our work, we construct three types of artificial data. The first type shifts between sessions but keeps stationary within one session (SHIFT). The second type changes gradually in the course of a session without the initial shift (GRAD). The third type contains these two types of change (BOTH).

The separability of the data is indicated by a parameter r_{cls}, which is defined as follows:

$$r_{cls} = \frac{|\mu_1 - \mu_2| \sqrt{n_1 n_2}}{\sqrt{|(\Sigma_1 + \Sigma_2) \cdot \frac{(\mu_1 - \mu_2)}{|\mu_1 - \mu_2|}| (n_1 + n_2)}} \tag{8}$$

where $|\cdot|$ means the norm of a vector, and n_i denotes the number of trials in class $i \in \{1, 2\}$. The r_{cls} measures how well the two classes are separated. A bigger r_{cls} means that the two class means are further away from each other compared with the variance in this direction. We denote it as r_{cls} to indicate that it is about the separability of the two classes, which is different from the following r_{chg}.

The degree of nonstationarity of the data is indicated by r_{chg}, which is defined as follows:

$$r_{chg} = \frac{|\mu_{tr} - \mu_{te}|\sqrt{n_{tr}n_{te}}}{\sqrt{|(\Sigma_{tr} + \Sigma_{te}) \cdot \frac{(\mu_{tr}-\mu_{te})}{|\mu_{tr}-\mu_{te}|}|(n_{tr} + n_{te})}} \tag{9}$$

where the subscripts tr and te indicate the labelled training data set and the unlabelled test data set, respectively. This parameter can be interpreted as the difference between the training data and the test data. A bigger r_{chg} means that the test data are more different from the training data, i.e., the nonstationarity is severer.

B. Data of BCI Competition IV

The data set IIb of BCI competition IV is provided by Graz University of Technology, Austria. It consists of EEG data from nine subjects, with five sessions for each subject. The task of the experiment is two class motor imagery. Details of the data and experimental setup can be found in [18].

IV. RESULTS AND DISCUSSION

For both artificial and real data, we check the performances of five methods, namely, a static LDA classifier without adaptation (STATIC), supervised adaptation (SUPER), incremental adaptation (INCRE), GMM based adaptation (GMM), and the proposed FCM based approach (FCM). Hyper-parameters in each methods are optimized based on the training data.

A. Artificial data

The artificial data have three sessions in each data set, with the first one as a training session and the other two as test sessions. By varying r_{cls} and r_{chg} each among 15 degrees, we get 225 groups of data sets, each group with fixed r_{cls} and r_{chg} level. In each group ten data sets are constructed, therefore we have 2250 data sets for each data type (SHIFT, GRAD, and BOTH).

Table I shows the averaged error rates of all the methods on the three types of artificial data. The results for real data (indicated as BCI4) are also shown for the purpose of comparison. The error rates in this table are averaged over all data sets with the same data type. From this table we can see that, for all data types our method shows a significant better performance than INCRE and GMM, and a comparable performance to SUPER.

In Fig.1, the effects of separability and nonstationarity on the performance of different methods are shown. For each fixed r_{cls} value, the error rates are averaged over all r_{chg} values, and vice versa. From Fig.1(a) we can see that, when r_{chg} is big (or the nonstationary is severe), FCM shows a much lower error rate than other unsupervised methods, which

TABLE I
ERROR RATES OF THE METHODS ON DIFFERENT TYPES OF ARTIFICIAL DATA AND REAL DATA.

Data type	STATIC	SUPER	INCRE	GMM	FCM
SHIFT	0.334	0.270	0.331	0.302	0.275
GRAD	0.335	0.284	0.334	0.303	0.274
BOTH	0.335	0.272	0.333	0.304	0.274
BCI4	0.208	0.194	0.204	0.202	0.195

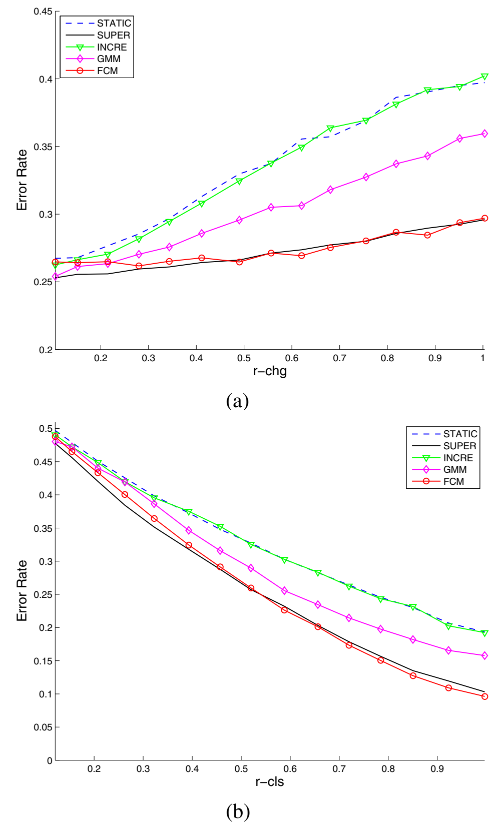

Fig. 1. Effect of data properties on the performances of each methods. The horizontal coordinate is r_{chg} or r_{cls}, and the vertical coordinate is error rate. Data type BOTH. We do not show the plots for SHIFT and GRAD, since the similar phenomenon can be found. (a) Effect of nonstationarity; (b) Effect of separability.

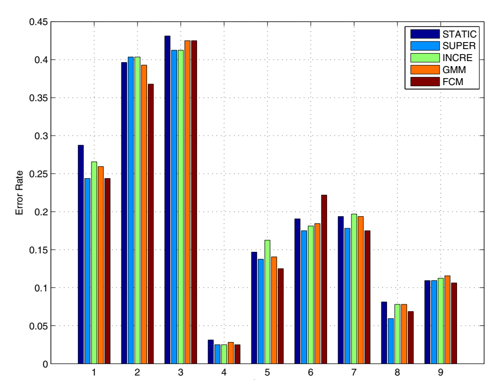

Fig. 2. Error rates of the nine subjects, data set IIb of BCI competition IV.

means that FCM is more adaptive to changes. However, when r_{chg} is very small (or the data are quite stationary), none of the unsupervised methods shows a noticeable improvement over STATIC. The reason may be that in this situation, a static classifier is good enough, while a complex unsupervised algorithm which needs parameter estimation will introduce computing error and result in a worse performance. From Fig.1(b) we can see that, when r_{cls} is big (or the two classes are well separated), FCM achieves a error rate comparable to SUPER, which is much lower than other unsupervised methods. This means FCM can effectively discover the class information from unlabelled data, as long as the two classes are well separated. However, when r_{cls} is small (or the two classes are badly separated), all the unsupervised methods including FCM do not show evident improvement over STATIC. This means if the data are essentially difficult to separate, then an advanced adaptation method will not help a lot. In such a case, more powerful feature extraction methods or even other BCI paradigms should be considered in order to achieve a satisfying result. In Fig.1 we only give the plot of data type BOTH, but not the plots of SHIFT and GRAD, since those plots show the similar phenomenon.

B. Data of BCI Competition IV

Using a CSP applied to signals from different frequency bands and a static LDA classifier (STATIC), we took part in the BCI Competition IV, and got the second place of data set IIb. In Fig. 2 the lowest error rate of each method for the nine subjects are shown. The results averaged over the subjects are show in the last row of Table I. From Fig. 2 we can see that for most subjects, FCM shows an improvement over STATIC, however the improvement is not as evident as for the artificial data. The reason may be that the BCI4 data are all very stationary, with an r_{chg} less than 0.2 for most subjects.

V. CONCLUSION

The nonstationarity of EEG signals is an important issue in the research of BCI. Various supervised adaptation methods have been reported to overcome this problem. However, in practical application, the real intention of the subject is not always known to the system, and unsupervised adaptation methods are needed. So far unsupervised adaptation methods for BCI have been reported by only a few works. In this paper, we adopt the FCM algorithm for unsupervised online adaptation of BCI. We checked the performance of this method on constructed artificial data. The proposed method achieves a better performance than other two existing unsupervised methods on the artificial data. At last, the methods are applied to real EEG data from data set IIb of the BCI Competition IV. The results of real data agree the analysis based on the artificial data. This confirms the effectiveness of our method. However, due to the good stationarity of the BCI4 data, the improvement is not so significant. Our future work will focus on experiments and the application of the proposed method to abundant real data with various properties.

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