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***Abstract*— Learning from other subjects and/or sessions led to considerable reduction of calibration time in EEG-based BCIs. However, such learning scheme is not straightforward because of the non-stationary nature of EEG signals. In this paper, we propose an adaptive accuracy-weighted ensemble (AAWE) approach that allows tracking non-stationarity in EEG signals and effectively learning from other subjects. It consists of an ensemble of classifiers, each of which is trained using data recorded from one BCI user. Classifiers' weights are initialized according to their accuracy in classifying calibration data of current BCI user. These weights are updated using ensemble decision during feedback phase, when there is no information about true class labels. The effectiveness of our approach is demonstrated through an empirical comparison with other state of the art classifiers combination strategies.**

Keywords: Brain-computer interfaces (BCIs), Electroencephalography (EEG), non-stationarity, transfer learning, ensemble methods.

I. INTRODUCTION

Brain-computer interfaces (BCIs) are communication and control technologies that enable their users to interact with external environment without using the peripheral neuromuscular system, by directly monitoring electrical and/or hemodynamic activity of the brain. Electroencephalography (EEG) is the most widely used technique in BCIs because of its high temporal resolution and low cost. Nevertheless, EEG signals present both a very low spatial resolution and a poor signal-to-noise ratio which makes brain activity patterns decoding very difficult. Thus, a time consuming calibration phase is necessary before every use of a BCI. During this phase, users are instructed to perform repeatedly predefined cognitive tasks in specified time periods (called trials) in order to collect enough labeled data used to build a robust classification model. This model will be used to classify new trials in a feedback phase during which users interact with the application at free will (label information is not provided).

Because long calibration phase is a limitation to the use of BCI technology in realistic interaction settings, many machine learning approaches have been attempted in order to build out-of-the-box classification models that can achieve good performance using a small calibration set. Among them, approaches based on transfer learning have attracted much attention during the last years [1-8]. They consist of incorporating data recorded from different subjects and/or during previous recording sessions in the learning process of current BCI user. However, these approaches are challenged by the non-stationarity of EEG signals recorded from different subjects and even during different sessions of the same subject (called inter-subjects and inter-sessions variability, respectively). Ensemble methods have been shown to be one of the most promising techniques for alleviating the problem of inter-subjects and inter-sessions variability as they allow modeling different brain activity patterns simultaneously [1-3]. *Fazli et al* [1] used an ensemble strategy in which a sparsification technique is applied in the classifiers combination step in order to find brain activity patterns that are common across all BCI users and "robust" to non-stationarity. Although this approach allowed reducing considerably calibration time for able-bodied users, the assumption of common underlying brain activity pattern may be very strong for disabled users as shown in [6]. As the physical properties of the sensors and the neurophysiological state of the user may change within the same recording session, Tu and Sun [2] proposed and "adaptive" ensemble framework in which classifiers' weights are dynamically estimated after receiving each feature vector during the feedback session of current BCI user. The weight of each classifier is proportional to its performance in classifying trials in the neighborhood of the received feature vector. Another dynamically weighted ensemble approach was proposed by Liyanage et al [3] for inter-sessions classification. Base classifiers are learned using clustered data of a previous recording session and classifiers' weights are estimated for each feature vector in the current session according to its distance to clusters' centers in each class. The two previous approaches are based on data independence assumption and do not take into consideration the fact that time-contingent feature vectors undergo the same sources of non-stationarity.

In this paper, we propose a new ensemble framework for inter-subjects classification in EEG-based BCIs in which we address the following issues:

- Reducing calibration time in BCIs using data recorded from different users.
- Managing inter-subjects variability of EEG signals through an accuracy-weighted ensemble strategy.
- Tracking EEG signals non-stationarity within the same session using a new unsupervised

- classifiers' weights update strategy based on ensemble decision.

II. NOTATIONS

In this work, we used Common Spatial Patterns (CSP) algorithm for feature extraction [9], but our approach applies to other feature extraction techniques for EEG classification. Due to space limitation, details of this algorithm are omitted.

Denote a multichannel EEG measurement of one trial as a t×n matrix X, where t is the number of samples per trial and n the number of electrodes. Let $^{2m\times n}$ be a filter bank learned from previous labeled trials using CSP algorithm, where m is the number of most discriminative spatial filters from each class in binary classification. The logarithmic variance feature vector of trial X is calculated as follows:

$$=\log(\frac{\mathrm{diag}\big((\qquad\qquad)\big)}{\mathrm{trace}\big((\qquad\qquad)\big)} \tag{1}$$

Where X' and W' are the transposes of matrices X and W, diag returns the diagonal elements of the square matrix and trace returns the sum of these elements.

Let $h^1,h^2,\ldots,h^K$ and $W^1,W^2,\ldots,W^K$ be the classification models and the filter banks learned using EEG signals recorded from K BCI users that previously performed the same cognitive tasks. Let h^{K+1} and W^{K+1} be the classification model and filter bank learned using calibration set of current user. The labeled logarithmic variance feature vectors of trials recorded during calibration phase of current BCI user filtered using filter bank of subject k are denoted $L^k=\{(x_1^k,y_1),\ldots(x_l^k,y_l)\}$, k 1, where l is the size of calibration set. For simplicity of notation, we replace x_i^k by x_i for the rest of the paper.

III. METHODS

In this section we describe our framework and show how it can deal with non-stationarity in EEG signals. Our approach is based on accuracy-weighted ensemble method which has been shown to be an efficient way for mining concept-drifting data streams [10]. We extend this method to transfer learning and propose a new classifiers' weights update strategy for dealing with data drifts within the same session without having any information about true class labels.

A. Accuracy-weighted ensemble

Given a trial and its true class label y, the classifier h^k, k=1…K+1 outputs the value $h_y^k(x) \in [0\ 1]$, which is an estimation of the conditional class probability p(y/x). Classification error of classifier h^k for trial X is then $-h_y^k(x)$. Since our goal is to efficiently combine data from different BCI users in order to reduce the size of calibration set of current user, the weight of each base learner should be proportional to its accuracy in classifying data from current user. Given the mean squared error of the base learner h^k, k …K, on calibration data of current user:

$$^k \quad \frac{}{|L^k|}\sum_{i,y_i)\in L^k} \quad h_{y_i}^k(x_i) \tag{2}$$

Its weight can be expressed as follows:

$$w^k=\max \qquad ^r \qquad ^k \tag{3}$$

Where ^{r} is the mean squared error of a random classifier which is calculated as follows:

$$^r=\sum_y p(y) \quad -p(y)) \tag{4}$$

For two classes classification with equal class priors, ^{r} 5.

Classifiers with accuracy less or equal than random classifier will be assigned weight 0 and the weights of other classifiers will be inversely proportional to their error in classifying calibration data of current user.

The classifier h^{K+1} learned using calibration set of current user is weighted in the same way by performing leave one trial out cross-validation. Including this classifier in the ensemble allows avoiding "negative transfer" in case of experimented BCI users.

B. Updating classifiers' weights using ensemble decision

A classification model that performs well in classifying trials of calibration set may not achieve good classification performance in classifying trials of feedback set and conversely as data drifts may occur. Drifts are generally gradual and may cause a rotation or shift in the classification decision boundary [11]. Thus, updating base classifiers' weights during feedback phase is necessary for maintaining good classification accuracy. Given a new labeled trial (X_i, y_i), classifiers' weights can be updated as follows:

$$w^k(i)=\max \qquad ^r \qquad ^k(i) \tag{5}$$

Where,

$$^k(i) \tag{6}$$

$$\frac{}{i}\times\Big[(i-1)\times \quad ^k(i-1) \quad h_{y_i}^k(x_i))\ \Big]$$

Yet, in realistic interaction settings, BCI user modulates his brain activity patterns at free will and the classification model does not have any information about class labels of EEG signals recorded during feedback phase. Since ensemble decision is generally better than each base classifier's decision, provided that minimal performance and diversity conditions are met [12], we suggest using this decision to gradually update classifiers' weights after receiving every new feature vector during feedback phase. So, eq. (6) becomes:

$$ {}^{k}(i) \qquad \qquad (7) $$

$$ \frac{}{i} \times \Big[(i\text{-}1)\times \quad {}^{k}(i\text{-}1) \quad h^{k}_{e_i}(x_i)) \Big] $$

Where ensemble's decision e_i is the following:

$$ e_i = \mathrm{argmax}_{y_i}\Big(\sum_{k=} w^{k}(i\text{-} \quad h^{k}_{y_i} \quad {}_{i} \qquad (8) $$

C. *Controlling update rate using a tradeoff factor*

The classifiers' weights update strategy presented above may not be fast enough to track data drifts during feedback phase. Thus, we may put more weight on the second term of equation (7) than the first term. This can be performed using a tradeoff factor α as follows:

$$ {}^{k}(i) \quad \frac{}{i} \qquad \qquad (9) $$

$$ \Big[(i\text{-}1)\times \quad {}^{k}(i\text{-}1) \quad \times(i\text{-}1))\times \quad h^{k}_{e_i}(x_i))^{2} \Big] $$

When $\alpha = -\frac{}{i-1}$, the classifiers' weights are not updated. When $\alpha \approx 0$, the update rate is slow. As comes close to 1, the update rate increases.

The update rate in equation (9) depends on the number of trials already classified and its value at the beginning of online phase is greater than its value at the end of it. This is important for BCI application as data shift between calibration and online phases is more important than data shift during online phase [11].

IV. EVALUATION

In this section, our framework is evaluated using the publicly available data set 2A in BCI competition IV, provided by the Graz group [13].

A. *EEG data set*

The data set consists of EEG signals recorded using 22 Ag/AgCl electrodes from 9 subjects. Subjects were asked to perform four different motor imagery tasks: left hand, right hand, both feet and tongue movement imagery. For each subject, a training and a testing set were collected. Both sets comprise 72 trials of duration 7 s from each class. EEG measurements were band-pass filtered using a 5^{th} order Butterworth filter in the frequency band 8-30 Hz. Logarithmic variance features were extracted from the time segment 3-5 s after the beginning of each trial. For spatial filtering, we used the three most discriminative CSP filters from each class (m = 3).

B. *Results*

In order to assess classification performance of our adaptive accuracy weighted ensemble (AAWE) framework, we compared it to three different approaches named as follows:

- AWE: Accuracy weighted ensemble without updating classifiers' weights during feedback phase.
- DWEN: Dynamically weighted ensemble method in which classifiers' weights are updated for each trial in feedback phase according to their accuracy in classifying feature vectors in its neighborhood [2].
- DWEC: Dynamically weighted ensemble method in which classifiers' weights are updated for each trial in feedback phase according to its distance to the center of each class [3].

Note that the comparison targets only the classifiers weighting strategies used in [2] and [3]. Features extraction and classifiers training steps are the same for all approaches. Linear Discriminant Analysis (LDA) was used as a base learner in all experiments.

Table. I illustrates average classification accuracy for each approach when the size of the calibration set is relatively small (10 and 20 trials). Evaluation was performed offline using leave one subject out cross-validation. In each iteration, training sets of eight subjects and the first N trials (N=10, 20) of test set of the ninth subject were used to learn spatial filters and classifiers. The rest of trials in the test set of the ninth subject were used to update classifiers' weights in each approach. The last 30% of the test set was used for calculating classification accuracy in order to assess the performance of our approach in tracking EEG signals non-stationarity within the same session. The parameters used for calculating the neighborhood of each trial and adjusting the update rate in the DWEN and AAWE approaches, respectively, were varied gradually and the values giving best results are retained. In online settings, these parameters should be fixed beforehand. For the DWEC approach, the objective function allowing estimation of classifiers' weights according to the distance of each trial to the center of each class was optimized for each subject's dataset separately.

Classification performance of our AAWE approach demonstrates its effectiveness in tracking EEG signals non-stationarity compared to other methods. However, the choice of the parameter α giving best results is an important issue that is worth investigating in the future. In most cases, the trial-based classifiers weighting method used in DWEN failed in maintaining good classification accuracy as it is very sensitive to outliers. Even though the DWEC method has been shown to be effective for learning from a previous session [3], it performs poorly in inter-subjects classification as EEG signals recorded from different subjects are much more variable than signals recorded during different sessions of the same subject.

TABLE I. AVERAGE CLASSIFICATION ACCURACY OF THE ENSEMBLE LEARNING MODEL USING DIFFERENT CLASSIFIERS WEIGHTING STRATEGIES

	Size of calibration set = 10 trials						**Size of calibration set = 20 trials**					
	Left hand vs. Right hand	***Left hand vs. Feet***	***Left hand vs. Tongue***	***Right hand vs. Feet***	***Right hand vs. Tongue***	***Feet vs. Tongue***	***Left hand vs. Right hand***	***Left hand vs. Feet***	***Left hand vs. Tongue***	***Right hand vs. Feet***	***Right hand vs. Tongue***	***Feet vs. Tongue***
DWEC	0.64 (±0.15)	0.66 (±0.17)	0.63 (±0.13)	0.69 (±0.15)	0.63 (±0.14)	0.56 (±0.10)	0.66 (±0.17)	0.69 (±0.16)	0.65 (±0.16)	0.69 (±0.14)	0.66 (±0.15)	0.60 (±0.16)
DWEN	**0.69 (±0.15)**	0.69 (±0.17)	0.70 (±0.15)	0.65 (±0.15)	0.66 (±0.16)	0.57 (±0.12)	0.68 (±0.16)	0.69 (±0.17)	0.70 (±0.15)	0.66 (±0.15)	0.67 (± 0.16)	0.57 (±0.13)
AWE	0.66 (±0.17)	0.66 (±0.11)	0.74 (±0.15)	0.71 (±0.09)	0.71 (±0.16)	0.62 (±0.10)	0.68 (±0.17)	0.75 (±0.18)	0.76 (±0.14)	0.77 (±0.13)	0.75 (±0.18)	0.67 (±0.10)
AAWE	0.69 (±0.18)	**0.71 (±0.15)**	**0.78 (±0.17)**	**0.74 (±0.13)**	**0.74 (±0.17)**	**0.63 (±0.10)**	**0.72 (±0.16)**	**0.78 (±0.19)**	**0.77 (±0.16)**	**0.78 (±0.13)**	**0.79 (±0.16)**	**0.69 (±0.08)**

V. CONCLUSION

In this paper, we proposed a novel subject transfer framework for EEG classification. We used an accuracy-weighted ensemble method for aggregating data from different users and a classifiers' weights update strategy based on ensemble's decision. This update strategy is useful in realistic interaction settings when we do not have any information about true class labels. Moreover, it is different from state of the art classifiers aggregation strategies as it is not based on data independence assumption. Empirical evaluation showed that our approach allows reducing the effect of non-stationarity in EEG signals recorded from different subjects and during feedback phase of the same subject on classification accuracy.

In future work, we will try to find heuristics for fixing the parameter α controlling the update rate of our AAWE approach. This is may be based on the BCI user's capacity in modulating his sensorimotor rhythms and the type of the motor imagery task.

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