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Adaptive Classification in a Self-Paced Hybrid Brain-Computer Interface System

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Abstract— **As the characteristics of EEG signals change over time, updating the classifier of a brain computer interface, BCI, (over time) would improve the performance of the system. Developing an adaptive classifier for a self-paced BCI however is not easy because the user's intention (and therefore the true labels of the EEG signals) are not known during the operation of the system. For certain applications, it may be possible to predict the labels of some of the EEG segments using some information about the user's state (e.g., the error potentials or gaze information). This study proposes a method that adaptively updates the classifier of a self-paced BCI in a supervised or semi-supervised manner, using those EEG segments whose labels can be predicted. We employ the eye position information obtained from an eye-tracker to predict the EEG labels. This eye-tracker is also used along with a self-paced BCI to form a hybrid BCI system. The results obtained from seven individuals show that the proposed algorithm outperforms the non-adaptive and other unsupervised adaptive classifiers. It achieves a true positive rate of 49.7% and lowers the number of false positives significantly to only 2.2 FPs/minute.**

I. Introduction

A brain-computer interface (BCI) system allows humans to use their brain signals to control various devices such as a virtual keyboard [1] and an orthosis [2]. BCI systems can be operated in a synchronized mode or an asynchronous (*self-paced*) mode [3]. In a synchronized BCI system, the periods when a user can control the system are determined by the system itself. A self-paced BCI system, on the other hand, allows users to control the system whenever they desire. The system is designed to identify the users intentional control (IC) state from the no control (NC) periods. Here, IC periods are periods when the user intends to issue control. NC periods, on the other hand, are periods during which the user does not intend to activate the system such as when he/she is obtaining information from the computer screen, thinking about a problem, etc.

One problem encountered in designing a BCI system is that the inputs to the system, i.e. the electroencephalogram (EEG) signals, are non-stationary [4], [5]. Among the factors that may cause non-stationarities in the EEG signals are the changes in the user's mental states; the way the user performs the same mental task; and changes in electrodes' impedance. Due to the non-stationarities of the EEG signals, the statistical characteristics of the features used in a BCI system change over time [4], [5], [6]. Subsequently, this may affect the performance of the system. Thus, it is of great interest to design a BCI classifier that is able to adapt to the changes in the characteristics of the EEG features.

A BCI classifier can be adapted using three different approaches:

1) supervised: only labelled data are used to update the classifier;
2) semi-supervised: both labelled and unlabelled data are used to update the classifier;
3) unsupervised: only unlabelled data are used to update the classifier.

Several BCI groups have proposed solutions for the adaptation of BCI classifiers in a supervised manner [4], [5], [7]. Supervised adaptation requires the knowledge of the true labels of the EEG signals at the time of data recording, which is usually not the case in real life. This is because the user's intention is not known. In [4], [5], [7], the experiments are conducted in a synchronous manner, i.e., external cues are given to the users to issue a specific control command. Therefore, the true labels of the EEG signals for each control command (or trial) are known and can be used to update the classifiers. The main goal of these studies is to reduce the time a user takes to learn how to use the system by introducing mutual adaptation between the user and the BCI [4], [7].

Unsupervised BCI classifiers have also been proposed [6], [8], [9]. These classifiers are updated using the unlabelled EEG signals acquired at the time of data recording. Vidaurre *et al.* [6] and Blumberg *et al.* [8] propose an adaptive unsupervised classifier based on the LDA in a synchronized BCI system. The study in [6] shows promising results during online experiments. Another method that allows unsupervised adaptation is the use of covariate shift adaptation [9]. This method assumes that the feature distributions of training and testing sessions are different, while the conditional distribution of the labels of the EEG trials given the feature vectors remains unchanged [9]. However, Vidaurre *et al.* [6] show that the use of covariate shift adaptation does not improve the performance of their system significantly.

The studies discussed above focus on adaptive classification for *synchronized BCI systems*. To the best of our knowledge, adaptive classification in the context of a *self-paced BCI system* has not been explored much in the literature. Developing an adaptive classifier for a self-paced

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BCI system is more challenging. This is because the user's intention and thus the true labels of the EEG signals are not known at the time of data recording. Also, for certain self-paced applications such as text-entry, it is important to ensure that the number of false positives (FPs) generated by the system every minute (denoted as *time-normalized false positive rate or TNFPR* [10]) remains small when the user is using the system. This is because a system with a low TNFPR (ideally zero) can prevent user frustration [11].

One solution to the problems discussed above is to utilize information that is useful in predicting the labels of the EEG signals when updating a classifier. For example, the error potentials that are elicited in the users EEG signals when the BCI system generates a classification error [12], [8], the gaze information of the user (which can be obtained from an eye-tracker) [10], etc. Our preliminarily study in [10] is the first to propose an adaptive algorithm to update the classifier of a self-paced BCI in a supervised manner using EEG segments with predicted labels. These EEG labels are predicted using eye position information obtained from an eye-tracker. The eye-tracker is also used along with the self-paced BCI in a hybrid BCI system to operate a virtual keyboard. The adaptive classification algorithm in [10] successfully reduces the number of false positives generated by the system. For the dwell time of 0.0s (i.e., the user can activate the BCI immediately once he/she gazes at a letter/word), the system achieves an average true positive rate (TPR) of 36.8% and a TNFPR of 7.9 FPs/min. This TNFPR, however, is still too high for our application.

To further improve the performance of the adaptive classifier in [10], we introduce a new adaptive scheme and a method that automatically selects the parameters used in updating the adaptive classifier. We also look into solutions to updating the classifier either in a semi-supervised or supervised manner. Our results show that the proposed algorithm successfully achieves a significantly better performance when it is updated in a semi-supervised manner, i.e., a TPR of 49.7% and a TNFPR of 2.2 FPs/min (when the dwell time is 0.0s, i.e., the user can select a target immediately once he/she gazes at it).

In the next section, we briefly review the design of our hybrid BCI system. Next, Section 3 presents the proposed adaptive classification algorithm. Results are presented in Section 4 and Section 5 is dedicated to discussion and conclusions.

II. The Self-Paced Hybrid BCI System

Self-paced BCI systems can provide the users a more natural and flexible means for controlling an object [3]. Unfortunately, it is challenging to employ existing pure (i.e., non-hybrid) self-paced BCI systems for practical applications such as spelling with a virtual keyboard. The main reason is that these systems can only recognize a limited number of mental tasks as unique IC commands (mostly one or two) [11], [13], [14]. This number is not enough to operate a virtual keyboard efficiently as the possible number of letters that could be entered is much larger than two. Another reason is that most self-paced BCI systems generate a large number of false positives per minute during the NC periods, which is not desirable. To overcome these problems, we have proposed in [10] a hybrid system that combines a self-paced BCI with an eye-tracker to operate a virtual keyboard (i.e. the Dynamic Keyboard [15]).

To make a selection (i.e., a click operation) using the hybrid system, a user needs to gaze at the target for at least a specific period of time (called the dwell time). The user can then activate the self-paced BCI by performing a mental or motor task (which is an attempted hand extension in this study). When changes in the EEG signals due to an attempted hand extension are detected by the signal processing unit in the BCI, a click command (i.e., an IC command) is initiated [10]. Note that if the dwell time threshold is set to 0.0s, the user can select a target immediately once he/she gazes at it. The hybrid BCI system can overcome the Midas Touch' problem (especially when the dwell time is small), which is a major problem experienced by conventional eye-gaze interfaces [10]. The Midas Touch' problem is the difficulty of determining whether or not the user is intending to select a certain object as the user might be gazing at the object for reasons other than to enter it [16].

The self-paced BCI component of the hybrid system employs 15 monopolar EEG channels. EEG signals are continuously segmented with a 1-second sliding window, with an 87.5% overlap. The artefact detection algorithm is first applied to each EEG segment [17]. If artefacts are detected, then the artefact removal algorithm, which employs the stationary wavelet transform (SWT) with an adaptive thresholding mechanism, is applied to denoise the EEG signals [17]. Next, thirty combinations of bipolar EEG signals are generated by calculating the difference between adjacent monopolar EEG signals. The features extracted are the power spectral density of each bipolar signal computed by Fast Fourier Transform (FFT). A stepwise Linear Discriminant Analysis algorithm is then used to select the best discriminating features and a Linear Discriminant Analysis (LDA) algorithm is applied as a classifier.

In the next section, we present the proposed adaptive classification algorithm that is based on LDA.

III. Proposed Adaptive LDA (ALDA)

In our preliminary study on adaptive classification [10], we demonstrated that the information about the coordinates of the point of gaze (obtained from the eye-tracker) is useful in predicting the occurrence of NC states. For example, if the point of gaze does not fall within any of the boxes on the screen that contain a letter(s)/word that the user can choose (*denoted as region* R_{no}), then the user is most likely in an NC state. Such information is then used to update the bias $w0$ of the classifier during operation in a supervised manner.

In this study, we modify the adaptive classification algorithm to further improve the performance of the hybrid BCI system. The proposed modifications are as follows:

1) an artefact removal algorithm is applied to the EEG signals. This allows more EEG data to be available for

training and updating the classifier;
2) a new and improved criterion for predicting no control (NC) labels to EEG segments is introduced;
3) the adaptive scheme is modified and a new method that automatically selects the parameters used in updating the classifier is introduced.

Wwe also investigate the performance of the classifier when it is updated in a supervised and semi-supervised manner.

Next, we discuss when and how the proposed adaptive classifier (denoted as ALDA) is updated.

A. When to Update ALDA?

The adaptive LDA classifier ALDA is adaptively updated during online operation when newly acquired EEG segments are assigned NC labels. The NC labels are predicted using information obtained from the eye-tracker. The procedures are explained below:

1) Every 1-second EEG segment, which meets the following conditions is identified during the operation (testing) of the system and labelled as an NC state:
   a) the user's point of gaze is within the region R_{no} at the last sample of the EEG segment; or
   b) the user's point of gaze is within the region R_{no} for at least 50% of the samples from the EEG segment.

   The first condition is the condition used in our previous work [10] to update the classifier because the user is usually in an NC state if his/her point of gaze is within region R_{no}. In this study, the second condition is introduced because we found that under this condition, approximately 93.4% of those EEG segments obtained from the training data are in fact NC trials.
2) Next, for every N_{NC} EEG segments that are newly labelled as an NC state using the above conditions, the proposed adaptive classifier is adjusted.

B. How to Update ALDA?

The proposed adaptive classifier ALDA is adjusted so that it meets the following two goals: 1) the classifier can adapt to the potential changes in the characteristics of the EEG features and 2) the classifier can reduce the TNFPR of the hybrid BCI system so that the TNFPR is no larger than a target value (which is 2 FPs/min in this study).

1) Goal 1: To adapt to the potential changes in the characteristics of the EEG features, the hyperplane of the LDA classifier may be (a) rotated by adjusting the weight vector w or (b) shifted in parallel to the original hyperplane by adjusting the bias $w0$. In this study, we have investigated three different approaches to adjust w or $w0$ of the LDA classifier during the testing session (whenever N_{NC} newly assigned NC EEG segments are obtained):

1) ALDA_Retrain: update w [using Eq. (1)] and $w0$;

$$w^T = \Sigma^{-1}(\mu_1 - \mu_2) \tag{1}$$

   where μ_i is the mean value of class i, Σ is the pooled covariance matrix, and $i = 1, 2$.
2) ALDA_EM: update w [using the Expectation-Maximization (EM) algorithm] and $w0$;
3) ALDA_Bias: only update $w0$.

The algorithm we proposed to adjust $w0$ is described later in the next subsection.

Both ALDA_Retrain and ALDA_Bias update the classifier in a supervised manner. ALDA_EM, on the other hand, updates the classifier in a semi-supervised manner where the EEG segments with unknown labels and those with predicted NC labels are used to update the classifier. In ALDA_EM, the EM algorithm is used to adaptively estimate the class prior probability (π_i), the class mean and the covariance of the data (μ_i, and Σ) [18]. These estimates are then used to update the LDA classifier. The followings explain how the EM algorithm estimates π_i, μ_i, and Σ (note that the initial parameters for the EM algorithm are estimated from the training data):

- Expectation step: the conditional probability of having class c_i given the feature vector at time n, x_n, denoted as $p(c_i|x_n)$ is updated as follows:

$$p(c_i|x_n) = = \begin{cases} Z_{ni} & \text{if label is known} \\ \frac{\pi_i p(x_n|c_i)}{\Sigma_{i=1}^{2} \pi_i p(x_n|c_i)} & \text{otherwise} \end{cases} \tag{2}$$

  where:

$$Z_{ni} = \begin{cases} 1 & \text{if } x_n \text{ (from the training data) } \in \text{class } i \\ 0 & \text{otherwise} \end{cases}$$

  and

$$p(x_n|c_i) \propto e^{-\frac{1}{2}(x_n-\mu_i)'\Sigma^{-1}(x_n-\mu_i)}$$

- Maximization step: π_i, μ_i, and Σ are updated as follows:

$$\pi_i = \frac{1}{Ns}\sum_{n=1}^{Ns} p(c_i|x_n)$$

$$\mu_i = \frac{1}{\pi_i Ns}\sum_{n=1}^{Ns} x_n p(c_i|x_n) \tag{3}$$

$$\Sigma = \frac{1}{Ns-1}\sum_{i=1}^{2}\sum_{n=1}^{Ns} p(c_i|x_n)(x_n-\mu_i)(x_n-\mu_i)'$$

  where Ns is the number of samples used to estimate the parameters in the EM algorithm.

2) Goal 2: To ensure that the TNFPR of the hybrid BCI system achieves a low target value (which is 2 FPs/min in this study), the hyperplane of the LDA classifier may need to be shifted in parallel to the original hyperplane (i.e., the bias $w0$ of the classifier is adjusted). For ALDA_Retrain, ALDA_EM and ALDA_Bias, the bias $w0$ is adjusted automatically such that the performance of the BCI component measured by TNFPR$_{BCI}$ is equal to a certain value, T_{FP} FPs/min. TNFPR$_{BCI}$ is defined as:

$$\text{TNFPR}_{BCI} = \left(1 - \frac{NC_{Correct}}{NC_{Train} + NC_{New}}\right) \times O_s \times 60 \tag{4}$$

where $NC_{Correct}$ is the number of correctly classified NC trials; NC_{Train} is the total number of NC trials from the training data; NC_{New} is the number of new trials from the testing session that are assigned NC labels and O_s is the number of outputs produced by the system per second (which is 8 in this study).

Note that the TNFPR of the hybrid system's BCI component, TNFPR$_{BCI}$ is different from the TNFPR of the hybrid system defined below:

$$\text{TNFPR} = (1 - \frac{NC_{Correct} + NC_{Sleep}}{NC_{Test}}) \times O_s \times 60 \quad (5)$$

where NC_{Sleep} is the number of trials when BCI is in a sleep mode; NC_{Test} is the total number of NC trials evaluated during testing.

As the TNFPR of the hybrid system is not known during online operation, the TNFPR$_{BCI}$ is used as a criterion to adjust the bias $w0$. By reducing TNFPR$_{BCI}$, the TNFPR of the hybrid BCI system will be reduced as well. The algorithm for adjusting the bias $w0$ of the LDA classifier is summarized below:

1) With the newly updated w (for ALDA_Retrain and ALDA_EM) and the original w (for ALDA_Bias), find the TNFPR$_{BCI}$.
2) If TNFPR$_{BCI}$ $> T_{FP}$ FPs/min, $w0$ is modified as follows and the TNFPR$_{BCI}$ is recalculated:
$$w0 = w0 - \kappa w0. \quad (6)$$
3) While TNFPR$_{BCI}$ $< T_{FP}$ FPs/min, $w0$ is modified as follows and the TNFPR$_{BCI}$ is recalculated:
$$w0 = w0 + \kappa w0. \quad (7)$$
where κ is the update rate for adjusting $w0$ ($0 < \kappa < 1$). The larger the κ value, the faster the algorithm converges. The value $\kappa = 0.05$ is used in this study because the adjustment needed is usually small. We found experimentally that values of κ larger than 0.1 sometimes over-adjust w0 and result in a very small TNFPR$_{BCI}$ and TPR, which is not desirable.

C. Data Description and Performance Evaluation

The EEG data used in this study are collected from the experiments described in [10]. For every participant, the EEG data collected from all sessions he/she completed (n_s sessions) are divided into three parts:

1) training data: the EEG data obtained from session 1 to $n_s - 2$, where n_s is the total number of sessions;
2) cross-validation data: the EEG data obtained from session $n_s - 1$;
3) testing data: all the EEG data obtained from the last session.

The LDA classifier is first trained using the training data. The values for the parameters N_{NC} and T_{FP} in the proposed adaptive classification algorithm are chosen automatically using the cross-validation data:

1) The target TNFPR$_{BCI}$ value, T_{FP}, is varied from 2 to 20 such that the TNFPR of the hybrid BCI system [defined in Eq. (5)] is 2 FPs/min. This is the target TNFPR value we wish to achieve when the system is evaluated using the testing data. If the user prefers a smaller TNFPR, we can then set the target TNFPR to a smaller value.
2) The procedure above is performed for two different update frequency N_{NC} values: 50 and 100 samples. The value of N_{NC} that gives the best performance of the hybrid BCI system is selected.

Finally, the performance of the proposed algorithm is tested in an online-like manner, i.e., all EEG segments of the testing session are used. The performance of the algorithm is evaluated using true positive rate (TPR) and TNFPR [defined in Eq. (5)]. TPR is the percentage of IC trials that are correctly detected by the system. An IC command (i.e., an attempted hand extension in this study) issued by a user is called an IC trial. A true positive (TP) is declared as present when the classifier correctly recognizes an IC state at least once in a TP window, i.e., the window from 0.5s before to 1.0s after a hand switch activation [19], [10], [17]. The EEG segments that do not overlap with the TP window are labelled as NC trials. Any detection of an IC state by the classifier that occurs outside the TP window is considered to be a false positive (FP).

In this study, we have compared the performance of the proposed methods (ALDA_EM, ALDA_Retrain, ALDA_Bias) with that of a non-adaptive classifier (LDA_Original) and three other state-of-the-art adaptive classification methods (PMean, PMean-GCov, EM):

1) LDA_Original: the LDA classifier, without any adaptation.
2) Unsupervised LDA - PMean (proposed in [6]): Readjust the bias $w0$ of the LDA classifier from sample to sample. $w0$ is modified by updating the average μ of the two class means. The average mean μ at time t is estimated by [6]:
$$\mu_t = (1 - \eta)\mu_{t-1} + \eta x_t \quad (8)$$
where η is the updating coefficient; x_t is the new feature vector (IC or NC) obtained at time t. Then, the bias is updated as follows:
$$w0_t = -w^T(\mu_t) \quad (9)$$
η is varied from 0.001 to 0.1 and is chosen automatically using the cross-validation data. The value of η that gives the best performance of the hybrid BCI system is selected.
3) Unsupervised LDA - PMean-GCov (proposed in [6]): adaptively update the weight vector w and the bias $w0$ of the LDA classifier on a sample-by-sample basis.
The bias $w0$ is updated using Eq. (9). Also, w is modified by updating the inverse of the global sample covariance matrix Σ_t^{-1} following [6]:
$$\Sigma_t^{-1} = \frac{1}{(1-\eta)}(\Sigma_{t-1}^{-1} - \frac{v_t v_t^T}{\frac{1-\eta}{\eta} + x_t^T v_t}) \quad (10)$$

where $v_t = \Sigma_{t-1}^{-1} x_t$. Then, the weight vector w_t is modified as follows:

$$w_t = \Sigma_t^{-1}(\mu_1 - \mu_2) \tag{11}$$

Similar to PMean, η is varied from 0.001 to 0.1 and is chosen automatically using the cross-validation data. The value of η that gives the best performance of the hybrid BCI system is selected.

4) Unsupervised - EM (proposed in [8]): adaptively update the LDA classifier using the EM algorithm.
5) Semi-supervised - the proposed ALDA_EM.
6) Supervised - the proposed ALDA_Retrain.
7) Supervised - the proposed ALDA_Bias.

In this study, a moving average filter (with the length of 2 samples) and a debounce block are applied to the output of all the classifiers to further improve the detection performance [11], [13]. Debouncing the BCI output is similar to the debouncing of a physical switch. After an activation is detected by the LDA, the LDA output is set to a state '1' for one sample. The next T_{db} samples, however, are forced to be the NC state '0', where T_{db} is the debounce period in samples. Similar to our previous study, a debounce component with a T_{db} of 8 decision samples is used here as well. Details of the BCI component are discussed in [10], [17].

IV. Results and Discussion

Table I compares the performance of the proposed methods (ALDA_EM, ALDA_Retrain, ALDA_Bias) with that of a non-adaptive classifier (LDA_Original) and three other state-of-the-art adaptive classification methods (PMean, PMean-GCov, EM). The TPR and TNFPR values are obtained from seven individuals. The dwell time used in the hybrid BCI system is 0.0s, which means that the user can select a target immediately once he/she gazes at it.

A one-way Analysis of Variance (ANOVA) is carried out to examine the statistical significance of the results. ANOVA shows that the mean performances of the hybrid BCI system with different classification methods are significantly different at a significance level of 0.01. As shown in Table I, the hybrid BCI system with LDA_Original has an average TPR = 80.3% and TNFPR = 11.3 FPs/min. With the unsupervised classifiers (PMean, PMean-GCov, and EM) the average TPR and TNFPR achieved are (82.6%, 14.4 FPs/min), (77.3%, 9.6 FPs/min) and (75.3%, 9.7 FPs/min) respectively. The proposed method ALDA_EM, on the other hand, successfully reduces the average TNFPR to around 2.2 FPs/min even though the TPR is reduced to 49.7%. The performance of ALDA_EM, ALDA_Retrain and ALDA_Bias are not significantly different. ALDA_Bias, however, is computationally the least expensive.

There is always a trade-off between the TPR and the TNFPR. A higher TPR can be achieved at the expense of having a higher TNFPR. However, a system with a low TNFPR (even if that may result in a lower TPR) is more desirable. The reason is that when operating the Dynamic Keyboard using the self-paced hybrid system, a false positive would result in selecting the wrong target. Consequently, the user has to initiate additional commands to de-select the wrong target and then select the correct desired target. On the other hand, in case of a missed IC, the user only has to issue the IC command again. This explains the reason why a system with a low TNFPR (even if that may result in a lower TPR) can reduce user frustration.

PMean, PMean-GCov, and EM do not perform as well when applied to self-paced BCI system mainly because these algorithms are originally proposed for synchronized BCI systems [6], [8]. A synchronized BCI system is designed to discriminate two or more intentional control (IC) states. It does not recognize the no control (NC) state. In this context, no mechanism is needed in the BCIs classifier to ensure that the system generates a low number of false positives per minute. In contrast, a self-paced BCI system discriminates the IC state against the no control (NC) state. Achieving a low TNFPR is important to reduce user frustration (as discussed earlier). Therefore, unlike a synchronized BCI system, a mechanism is needed in a self-paced BCI system to ensure that the TNFPR is low. Such a mechanism is found in our proposed adaptive classification algorithm. With the use of this mechanism, the TNFPR of the self-paced hybrid BCI system is reduced significantly.

We also find the Receiver Operating Characteristic (ROC) curves for the non-adaptive LDA Original. An ROC curve is found offline by adjusting the decision threshold of the classifier (i.e., $w0$) when the classifier is tested on testing data. From the ROC curves, when the TNFPR of LDA_Original is around 2.0 FPs/min, the average TPR is 44.7%. The performance of ALDA_EM, ALDA_Retrain and ALDA_Bias (which allows online adaptation) achieves higher TPRs and a TNFPR of around 2.0 FPs/min. This shows that the proposed adaptive methods not only reduce the TNFPR of the hybrid BCI system, but also improve the TPR.

Finally, we investigate the processing time for the proposed methods. In this study, all algorithms are run in Matlab 2009b environment. The processor used is a 2.93 GHz Intel (R) Core i7 870. The proposed hybrid BCI system processes the EEG segments every 125 ms (i.e., 8 outputs are generated every second). Therefore, all the signal processing algorithms have to be executed within 125 ms. The artefact detection, artefact removal and FFT feature extraction algorithms take approximately 4 ms, 30 ms, and 3 ms respectively, to process a 1-second EEG segment with 15 channels. Both ALDA_Retrain and ALDA_Bias are simple and computationally efficient. ALDA_Retrain requires no more than 50 ms to update the classifier. ALDA_Bias only involves adjusting the bias, i.e., shifting the hyperplane in parallel to the original hyperplane. Hence, its computational time is significantly smaller (an average of 6.1 ms). When either of the proposed adaptive classification algorithms is incorporated into the BCI, the total processing time for all signal processing algorithms is less than 100 ms, which is suitable for real-time processing. We expect these numbers to be significantly improved if the algorithm is implemented in C++ environment, which is more suitable for online

TABLE I

COMPARING THE PERFORMANCE OF PROPOSED ALDA WITH OTHER CLASSIFICATION METHODS (DWELL TIME = 0.0S).

Subject	(TPR:%, TNFPR:FPs/min)						
	Non-Adaptive	Unsupervised			Semi-Supervised	Supervised	
	LDA_Original	PMean-GCov	PMean	EM	*ALDA_EM*	*ALDA_Retrain*	*ALDA_Bias*
AB1	(93.4,27.0)	(93.4,27.0)	(86.8,16.9)	(93.4,27.4)	(61.8,3.0)	(59.2,3.4)	(60.5,3.4)
AB2	(94.3,16.9)	(75.9,14.2)	(50.6,1.9)	(93.1,14.6)	(54.0,3.5)	(60.9,4.5)	(48.3,4.9)
AB3	(89.8,7.5)	(87.8,9.8)	(83.7,3.7)	(87.8,4.9)	(70.4,2.3)	(70.4,1.2)	(72.4,1.6)
AB4	(79.3,3.6)	(84.7,8.6)	(88.1,10.1)	(78.0,4.0)	(64.4,1.4)	(57.6,1.0)	(61.0,1.3)
AB5	(77.2,7.5)	(82.6,10.1)	(82.6,9.3)	(57.6,4.6)	(35.9,1.8)	(34.8,2.2)	(37.0,2.0)
AB6	(62.0,8.2)	(76.9,16.1)	(77.7,15.4)	(62.0,8.2)	(26.4,2.1)	(27.3,2.3)	(28.1,2.1)
AB7	(70.0,8.6)	(78.8,15.0)	(71.3,9.6)	(55.0,4.2)	(35.0,1.2)	(23.8,1.0)	(28.7,1.2)
Mean	**(80.3,11.3)**	**(82.9,14.4)**	**(77.3,9.6)**	**(75.3,9.7)**	**(49.7,2.2)**	**(47.7,2.2)**	**(48.0,2.4)**

applications. ALDA_EM, on the other hand, requires more than 300 ms processing time, which is more computationally expensive compared to ALDA_Retrain and ALDA_Bias. This processing time can definitely be reduced if implemented in C++.

V. CONCLUSIONS

We propose a fully automated algorithm to adaptively update the LDA classifier in our self-paced hybrid BCI system. The proposed adaptive classification algorithms are either updated in a supervised or semi-supervised manner. This necessitates the knowledge of the labels of some of the EEG segments during the time of data recording. In this study, the labels of some of the EEG segments are predicted using the eye position information obtained from the eye-tracker. This approach to predicting the EEG labels is easy and has shown to be effective. In addition, the eye-tracker data is readily available from our hybrid system. For pure BCI systems that do not have an eye-tracker, the proposed adaptive algorithm can still be applied before the labels of the EEG segments are predicted using other different methods. For example, when an error is generated by the system, the labels of the EEG segments can be deduced using the error potentials that are detected in the EEG signals; or the labels can also be deduced using other information extracted from the EEG/EOG signals such as the types of artefacts detected, eye position, etc.

As part of future work, we are interested in investigating the possibility of predicting the IC labels during online operation. This may be achieved by utilizing information such as the cursors information, how long the user gazes at a point and whether or not a letter/word is selected. In addition, the acceptable TNFPR for operating a virtual keyboard using the self-paced hybrid BCI system is not known. This issue is important and need to be addressed before online studies are conducted to investigate the usability of the performance of the system.

REFERENCES

[1] R. Scherer, G. R. Müller, C. Neuper, B. Graimann, and G. Pfurtscheller, "An asynchronously controlled EEG-based virtual keyboard: improvement of the spelling rate," *IEEE Trans. on Biomed. Eng.*, vol. 51, no. 6, pp. 979–1307, 2004.

[2] G. Pfurtscheller, C. Guger, G. Müller, G. Krausc, and C. Neuper, "Brain oscillations control hand orthosis in a tetraplegic," *Neuroscience Letters*, vol. 292, pp. 211–214, 2000.

[3] S. G. Mason and G. E. Birch, "A brain-controlled switch for asynchronous control applications," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 10, pp. 1297–1307, 2000.

[4] J. d. R. Millán, "On the need for on-line learning in brain-computer interfaces," in *Proceedings of the International Joint Conference on Neural Networks*, 2004.

[5] P. Shenoy, M. Krauledat, B. Blankertz, R. P. N. Rao, and K. R. Müller, "Towards adaptive classification for BCI," *J. Neural Eng.*, vol. 3, no. 1, pp. R13–23, 2006.

[6] C. Vidaurre, M. Kawanabe, P. von Bünau, B. Blankertz, and K. R. Müller, "Toward unsupervised adaptation of lda for brain-computer interfaces," *IEEE Trans. on Biomed. Eng.*, vol. 58, no. 3, pp. 587–597, 2011.

[7] C. Vidaurre, A. Schlögl, R. Cabeza, R. Scherer, and G. Pfurtscheller, "Study of on-line adaptive discriminant analysis for EEG-based brain-computer interfaces," *IEEE Trans. on Biomed. Eng.*, vol. 54, no. 3, pp. 550–556, 2007.

[8] J. Blumberg, J. Rickert, S. Waldert, A. Schulze-Bonhage, A. Aertsen, and C. Mehring, "Adaptive classification for brain computer interfaces," in *IEEE EMBS*, 2007.

[9] Y. Li, H. Kambara, Y. Koike, and M. Sugiyama, "Application of covariance shift adaptation techniques in brain-computer interfaces," *IEEE Trans. on Biomed. Eng.*, vol. 57, no. 6, pp. 1318–1324, 2010.

[10] X. Yong, M. Fatourechi, R. K. Ward, and G. E. Birch, "The design of a point-and-click system by integrating a self-paced brain-computer interface with an eye-tracker," *IEEE JETCAS Special Issue on Brain Machine Interface*, vol. 1, no. 4, pp. 590–602, 2011.

[11] J. F. Borisoff, S. G. Mason, A. Bashanti, and G. E. Birch, "Brain-computer interface design for asynchronous control applications: improvements to the LF-ASD asynchronous brain switch," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 985–992, 2004.

[12] A. Buttfield, P. W. Ferrez, and J. dR. Millan, "Towards a robust BCI: error potentials and online learning," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 164–168, 2006.

[13] M. Fatourechi, R. K. Ward, and G. E. Birch, "Performance of a self-paced brain-computer interface on data contaminated with eye-movement artifacts and on data recorded in a subsequent session," *Computational Intelligence and Neuroscience*, 2008.

[14] A. Bashashati, R. K. Ward, and G. E. Birch, "Towards development of a 3-state self-paced brain-computer interface," *Computational Intelligence and Neuroscience*, 2007.

[15] "Dynamic Keyboard—CanAssist," http://www.canassist.ca/dynamic-keyboard.

[16] R. J. K. Jacob, "The use of eye movements in human-computer interaction techniques: what you look at is what you get," *ACM Transactions on Information Systems (TOIS)*, vol. 9, no. 2, pp. 152–169, 1991.

[17] X. Yong, M. Fatourechi, R. K. Ward, and G. E. Birch, "Automatic artefact removal in a self-paced hybrid brain-computer interface system," *Journal of NeuroEngineering and Rehabilitation*, 2012.

[18] T. Hastie and R. Tibshirani, "Disciminant analysis by gaussian mixtures," *J.R. Statist. Soc. B*, vol. 58, no. 1, pp. 155–176, 1996.

[19] A. Bashashati, M. Fatourechi, R. K. Ward, and G. E. Birch, "User customization of the feature generator of an asynchronous brain interface," *Annals of Biomedical Engineering*, vol. 34, no. 6, pp. 1051–1060, 2006.