

Learning Adaptive Subject-independent P300 Models for EEG-based Brain-Computer Interfaces

Shijian Lu, Cuntai Guan, and Haihong Zhang

Abstract— This paper proposes an approach to learn subject-independent P300 models for EEG-based brain-computer interfaces. The P300 models are first learned using a pool of existing subjects and Fisher linear discriminant, and then autonomously adapted to the unlabeled data of a new subject using an unsupervised machine learning technique. In data analysis, we apply this technique to a set of EEG data of 10 subjects performing word spelling in an oddball paradigm. The results are very positive: the adapted models with unlabeled data yield virtually the same classification accuracy as the conventional methods with labeled data. Therefore, it proves the feasibility of P300-based BCIs which can be applied directly to a new subject without training sessions.

I. INTRODUCTION

P300 is an endogenous, positive polarity component of the evoke-related-potential (ERP) elicited in the brain in response to infrequent/oddball auditory, visual or somatosensory stimuli in a stream of frequent stimuli. Farwell and Donchin [5] first demonstrated the use of P300 for brain-computer interfaces (BCIs) [1], [2] in a so-called oddball paradigm. In the paradigm, the computer displays a matrix of cells representing different letters, and flashes each row and column alternately. A user trying to input a letter needs to pay attention to the letter for a short while. In this process, when the row/column containing the intended letter flashes, a P300 will be elicited in EEG, which can then be detected for word spelling by an appropriate algorithm.

It is recognized that large inter-subject variations exist among people. For example, the amplitude and latency exists in both normals as well as clinical populations. And this has been linked to individual differences in cognitive capability. Therefore, from the pattern recognition viewpoint, computational P300 models build for one person would not apply well to another person [8]. To solve this problem, existing P300-based BCIs all use a direct method to solve this problem by training subject-specific P300 models. Thus, before a person can operate the BCIs, he/she needs to go through a special training process. In that process, the person usually follows instructions to stare at a particular cell at a given time, while his concurrent EEG is recorded. With the recorded data, a computer algorithm performs signal analysis and learns the subject-specific P300 model. However, this process is normally tedious and complicated.

This work consists of the first attempt to address this issue, in order to make future P300-based BCIs directly usable by a new subject without special training. The basic

assumption is that, despite the large inter-subject variations, people share common characteristics in their P300. Thus, a common P300 model can be established for general people. Next, it's interesting to study if it's possible to adapt this model to a particular subject's P300 in an unsupervised manner (thus the training processing is unnecessary).

In particular, our technical approach presented here consists of two steps. First, we use a set of labeled EEG data, from a number of subjects' training sessions, to build a linear classifier which discriminates between P300 and non-P300 EEG. Next, for a new subject, we develop an iterative procedure to update the classifier using the new EEG data from the particular subject.

We have tested the proposed approach on a data set of 10 subjects. The results are very positive: the adapted models with unlabelled data can yield virtually the same classification accuracy as the conventional methods with labeled data for most subjects studied. Therefore, it proves the feasibility of P300-based BCIs which can be applied directly to a new user without training sessions.

II. P300 SPELLER SETUP

The EEG used in this paper are collected from a P300-based speller described in [8]. In that speller system, a subject sitting in front of a 6×6 matrix of characters shown in Fig. 1 is equipped with a 64-channel EEG electro-cap. An electrolyte gel is particularly applied to the electrodes to reduce the impedance. The collected EEG is first amplified by a Neuroscan amplifier called SynAmps2 and then piped to a server by the Neuroscan software. Besides, 24 of the 64 channels are selected as described in [10] and the EEG sampling rate is set at 250 Hz.

The six rows and columns of characters in Fig. 1 flash successively and randomly. The subject needs to focus on one specific character visually within a specific number of flashing rounds. In particular, a round is defined here by the flashing all six rows and columns in a random order. And an epoch is defined by a period (typically 500 ms) right after each flash, during which EEG is measured and will be used for the later P300 detection. Therefore, two (one row flash and one column flash) out of the 12 flashes within each round indicate the focused character. The row and the column that specify the focused character can be determined by identifying the P300 within the collected EEG.

Ten subjects participate in our EEG collection. For each subject, two sessions of EEG are collected sequentially, which correspond to the input of the same set of 41 characters "THE QUICK BROWN FOX JUMPS OVER LAZY DOG

Shijian Lu, Cuntai Guan, and Haihong Zhang are with the Institute for Infocomm Research, Agency for Science, Technology, and Research (A*STAR), Singapore (email: {slu, ctguan, hhzhang}@i2r.a-star.edu.sg)



Fig. 1. Interface of the P300-based Word Speller.

246138 579” in two different orders. For each character, ten rounds of flashes are implemented. And within each epoch, EEG between 150 ms and 500 ms following the flash are used for the P300 identification. In the later discussion, we uniformly refer to the first and the second session EEG as the training and testing data, respectively.

III. PROPOSED EEG CLASSIFICATION TECHNIQUES

This section presents our proposed EEG classification technique. The EEG preprocessing is first described. A new EEG classification technique is then discussed, which trains an universal subject model by using EEG collected from a pool of subjects. Finally, an adaptive EEG classification technique is presented, which first builds a subject-specific model based on the subject’s EEG classified by the universal subject model and then uses the subject-specific model to classify the subject’s ensuing EEG.

A. EEG Preprocessing

The collected EEG needs to be preprocessed before the EEG classification. We first implement a low-pass filtering of the EEG by using an optimal cutoff frequency [9]. The filtered EEG is then down-sampled where every five consecutive EEG samples are averaged to a single EEG sample. Such down-sampling reduces the data size and so speeds up the ensuing processing greatly.

Ocular artifacts are then removed by treating the sampled EEG $y(n)$ as a linear superposition of the measured EOG $u(n)$ and the real EEG $w(n)$:

$$y(n) = \sum_{i=1}^N b_i u_i(n) + w_i(n) \quad (1)$$

where N is the number of sites at which the EOG measurement is done, two in our setup. In particular, we remove the EOG by using the difference model reported in [8], which removes the inter-sample correlations of the required EEG $w(n)$ as follows:

$$y(n) = y(n') + \sum_{i=1}^N b_i (u_i(n) - u_i(n')) + w_i(n) - w_i(n') \quad (2)$$

where $n' = n - 1$. Since the dynamic range of w is small in comparison to u , the propagation constants b_i can be computed through the least square minimization.

B. Boosted EEG Classification

We first study a new EEG classification technique that trains an universal subject model by using EEG collected from a pool of subjects. The universal subject model is based on the observation that different subjects normally share some common characteristics within their P300. As a result, an subject model trained by EEG of multiple subjects may capture such common characteristics and so can be used to classify EEG of a new subject with no training.

Different EEG classification strategies have been reported, among which SVM and Fisher’s linear discriminant (FLD) outperform others in most cases as evaluated in [12]. In our P300 speller, we use FLD for the EEG classification due to its lower computation cost. Before the EEG classification, a feature vector x is first created by concatenating EEG within the 24 selected channels as follows:

$$x = [x(1)^T, \dots, x(i)^T, \dots, x(N)^T]^T \quad (3)$$

where $x(i)$ refers to the EEG collected from the i -th selected channel and N is equal to 24.

For the two class case (with and without P300), the FLD simply classifies the EEG feature vector x to the class that minimizes the quantity below:

$$J = -2\hat{\mu}_k^T \hat{\Sigma}^{-1} x + \hat{\mu}_k^T \hat{\Sigma}^{-1} \hat{\mu}_k^T - 2\log\pi_k, \quad k = 1, \dots, K. \quad (4)$$

where $\hat{\mu}_k^T$ and $\hat{\Sigma}^{-1}$ refer to the mean and covariance of the EEG feature vectors, which can be estimated based on the collected EEG. The π_k is the a priori probability, which is equal to 1/6 or 5/6, respectively, for EEG with and without P300.

The construction of the universal subject model can be summarized as follows. First, a large amount of EEG is collected from a pool of subjects as follows:

$$D = \{[X_{s1}(i), Y_{s1}(i)], \dots, [X_{sn}(i), Y_{sn}(i)], i = 1, \dots, N\} \quad (5)$$

where X and Y refer to the collected EEG and the corresponding labels. N gives the epoch numbers of collected EEG. The terms $s1, \dots, sn$ refer to the subjects that participate in the EEG collection. A universal subject model is then trained by the pre-collected training EEG specified in Equation (5) above. Lastly, EEG of a new subject can be classified by using the universal subject model with no training. It should be noted that the data used for the model training above should be collected under the same protocol.

During the EEG classification, the universal subject model assigns each feature vector two scores, indicating the probability of the feature vector containing P300 or not. Therefore, the flash row and column within each round can be determined by the maximum score that indicates the existence of P300. As each character requires ten rounds of flashing described in Section 2, the subject selection can be determined by the maximum score averaged over the ten

rounds of intensification. Experimental result to be discussed in Section IV. B shows that compared with the simple cross-subject EEG classification, the proposed universal subject model augments the EEG classification significantly.

C. Adaptive EEG Classification

The universal subject model described in the last subsection is capable of classifying EEG of a new subject with no training. However, the classification accuracy is normally lower than that of the supervised model that is trained by EEG of the new subject. The accuracy degradation can be mainly explained by the fact that the universal subject model does not capture the EEG characteristics of the new subject. In this section, we will present an adaptive EEG classification technique, which first classifies subject EEG by using the universal subject model and then adapt the universal subject model to a subject-specific model in an unsupervised manner.

In our proposed technique, the subject-independence is achieved through a unsupervised learning process. Given a new subject, its EEG is first classified and labeled by using the universal subject model described in the last subsection. A subject-specific model is then trained by the classified EEG and the labels predicted by the universal subject model. After that, the subject-specific model is iteratively updated by the ensuing EEG of the subject and the labels predicted by the subject-specific model itself. Algorithm I below lists a few steps that implement the proposed adaptive EEG classification technique:

Algorithm I

Given A large amount of EEG D collected from a pool of subjects and a new subject S to be studied

Step 1. Build an universal subject model by using the pooled subject EEG D .

Step 2. For the new subject S , collect its initial session of EEG $\{X(i), i = 1, \dots, N\}$ and classify the collected EEG by using the universal subject model.

Step 3. Train a subject-specific model by using the initial session of the EEG $\{X(i), i = 1, \dots, N\}$ and the labels $\{Y(i), i = 1, \dots, N\}$ that are predicted by the universal subject model.

Step 4. Classify a specific amount of the ensuing EEG of S $\{X(i), i = N + 1, \dots, M\}$ by using the newly built subject-specific model.

Step 5. Update the subject-specific model by incorporating the newly classified EEG $\{X(i), i = N + 1, \dots, M\}$ and the labels $\{Y(i), i = N + 1, \dots, M\}$ predicted by the subject-specific model.

Step 6. Repeat Steps 4 and 5 for a specific number of iterations and then stop.

Though the proposed technique derives the subject-specific model through a unsupervised learning process, the idea is actually very similar to the semi-supervised learning [11], which is quite helpful when only a small amount of labeled training EEG is available. However, the main difference of our model adaptation technique to the semi-supervised learning is that it does not require any labels of EEG of the new subject. Instead it uses the labels that are predicted by

TABLE I
CROSS-SUBJECT CLASSIFICATION ACCURACY: THE FIRST ROW SHOWS EEG OF THE TEN SUBJECTS; THE FIRST COLUMN SHOWS TEN MODELS TRAINED BY EEG OF THE TEN SUBJECTS.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
M1	100	78	84	40	29	66	80	38	83	48
M2	93	98	85	44	16	41	61	84	60	44
M3	80	70	99	61	35	63	65	98	61	41
M4	48	40	43	100	7	57	62	61	78	34
M5	21	17	28	5	88	40	27	84	5	9
M6	32	12	10	15	32	98	37	72	16	18
M7	55	37	65	49	24	28	100	95	4	16
M8	21	44	48	29	29	44	63	100	6	6
M9	65	23	33	94	10	73	70	32	100	62
M10	56	56	56	18	16	33	32	85	41	96

the universal subject model. The ensuing model updating is then implemented in the similar way to the semi-supervised learning, which adapts a subject-specific model that greatly outperforms the universal subject model. The performance of the proposed adaptive EEG classification technique will be evaluated in the next section.

IV. EXPERIMENTAL RESULTS

This section presents experimental results of our proposed EEG classification techniques. The EEG variability among different subjects is first studied. The performance of the universal and adaptive EEG classification techniques is then evaluated and discussed. Throughout our experiments, all evaluations are based on EEG collected from the ten subjects as described in Section II.

A. Cross-Subject EEG Classification

Tough P300 ERP as a brain's built-in function is defined by a positive peak after 300 ms of an elicited stimuli, the real P300 of different subjects may vary greatly in term of the occurring time point as well as the peak amplitude. As a result, a P300 model trained by EEG of one subject may perform poorly over EEG of another subject. We use the cross-subject EEG classification to demonstrate the P300 variability among different subjects. In particular, ten subject models are first built by using the training (or testing data depending on the two-fold cross validation) EEG of the ten subjects. Each of the ten FLD models is then used to classify the testing (or training) EEG of the ten subjects, respectively. In above study, ten rounds of the EEG are all used during the model building and the cross-subject EEG classification.

Table I shows the classification accuracies calculated through the two-fold cross validation. In Table I, the rows 2-11 correspond to the ten subject models trained by EEG of each of the ten subjects. The columns 2-11 correspond to the testing (or training) EEG of the ten subjects. Therefore, the diagonal items in Table I give supervised accuracies, which are evaluated by using the models trained by the subject's own EEG. On the other hand, the non-diagonal items give the cross-subject accuracies, which are evaluated by using the models trained by other subject's EEG. Fig. 2 further

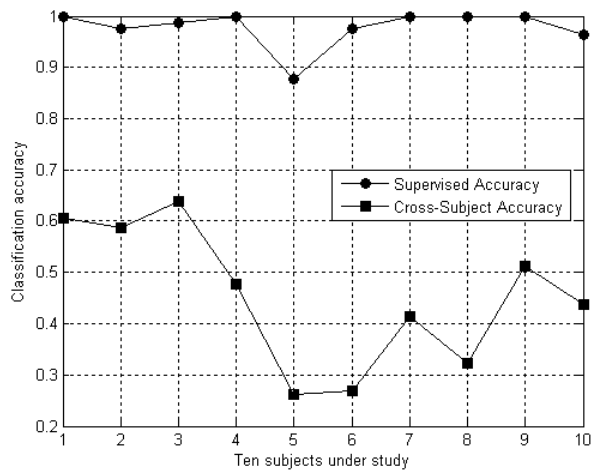


Fig. 2. Accuracy of the cross-subject model and the supervised model.

shows the supervised accuracies (diagonal items in Table I) and the cross-subject accuracies, the later of which are derived by averaging the items in Table I column by column excluding the diagonal items. Obviously, the supervised accuracies are significantly higher than the averaged cross-subject accuracies, indicating the EEG variability among different subjects.

In addition, the accuracies of the same EEG model over different subjects (items in each row) may be far different. For example, the classification accuracies of M2 (FLD model trained by EEG of the second subject) over S10 and S1 (EEG of the tenth and first subjects) reach 44% and 93%, respectively. Due to the P300 variability shown in Table I, a complicated training procedure is generally required for a P300-based word speller to capture the EEG individuality beforehand.

B. Universal & Supervised EEG Classification

The universal EEG classification technique described in Section III. B has been tested as well. We evaluate the universal subject model by using EEG collected from the ten subjects. First, ten universal subject models are built where each model is trained by EEG of every nine of the ten subjects as follows:

$$D_i = \{\cup T_j, \text{ for } j = 1, \dots, 10, \text{ where } j \neq i\}. \quad (6)$$

where T_j refers to the training data (or testing data depending on the two-fold cross-validation) of the j -th subject. Therefore, D_i refers to the EEG of nine subjects that are used to train the i -th universal subject model. The trained universal subject model is then used to classify the testing (or training) EEG of the remaining subject (i.e. the i -th subject).

Table II shows the classification accuracies when the round number increases from 1 to 10. As Table II shows, the universal model accuracies are generally much higher than those cross-subject accuracies (non-diagonal items) in Table

TABLE II
UNIVERSAL MODEL ACCURACY: THE FIRST ROW SHOWS THE TEN ROUNDS OF EEG; THE FIRST COLUMN SHOWS TEN UNIVERSAL MODELS TRAINED BY EEG OF EVERY NINE SUBJECTS.

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
S1	29	46	58	67	72	78	83	88	89	91
S2	25	40	48	60	66	72	75	77	84	88
S3	35	53	63	73	80	85	89	93	95	95
S4	28	44	57	66	77	82	84	88	88	88
S5	9	12	15	18	20	23	29	30	33	34
S6	29	44	57	68	72	79	84	89	90	90
S7	41	61	73	80	84	87	89	91	93	93
S8	38	60	75	80	89	93	97	98	98	100
S9	27	41	55	64	72	77	80	83	84	87
S10	18	28	38	45	52	60	65	71	75	79

I at the tenth round. On the other hand, the results in Table II also indicate that the performance of the universal subject model may vary greatly from subject to subject. For example, the accuracy of the universal subject model over the eighth and fifth subjects reaches 100% and 34%, respectively, at the tenth round.

Fig. 3 compares the accuracy of the universal subject model and the supervised model. In particular, the curves labeled by circles and squares indicates the supervised and universal model accuracy (the last column of Table II), respectively. As Fig. 3 shows, the supervised model accuracy is much higher than that of the universal subject model. Such results indicate the limitation of the universal subject model, i.e. it does not capture the subject-specific P300 characteristics. In addition, for some specific subject (i.e. the fifth subject), the accuracy of the universal subject model may even be unacceptable. This can be explained by the fact that the P300 of the fifth subject is quite different from the rest subjects. On the other hand, the universal model accuracy is generally much higher than the simple cross-subject model accuracy shown in Fig. 2.

C. Adaptive EEG Classification

We evaluate the performance of the adaptive classification technique by using EEG of the ten subjects as well. For each subject, its training data are first classified by using the universal model trained by EEG of the remaining subjects. A subject-specific model is then trained by the training EEG of the subject and the labels predicted by the universal subject model. After that, the testing data of the subject is classified by using the subject-specific model. Lastly, the above procedure is implemented again by switching the training and testing data for the purpose of cross-validation.

Fig. 4 shows the adaptive model accuracy described above. As Fig. 4 shows, the accuracy of the adapted model is significantly improved compared with the cross-subject models. In addition, the accuracy of the adaptive model is obviously higher than the universal subject model shown in Fig. 3. This verifies the effectiveness of the adaptive classification idea,

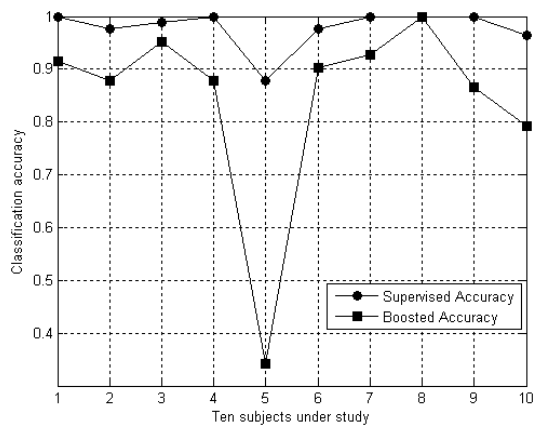


Fig. 3. Accuracy of the proposed universal subject model and the supervised subject model

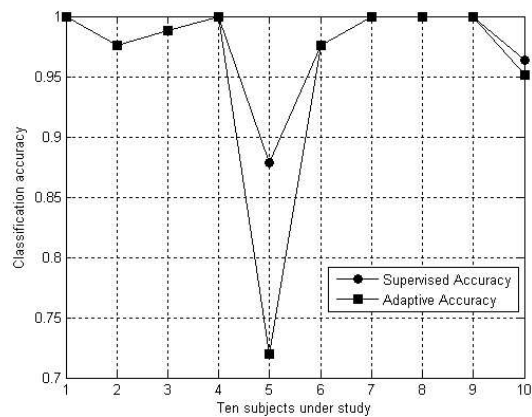


Fig. 4. Accuracy of the proposed adaptive subject model and the supervised subject model

namely, the inclusion of the subject's own EEG will improve the EEG classification greatly. More importantly, the adapted model achieves virtually the same performance as supervised model for most subjects under study.

However, we also observe that the fifth adapted subject model does not perform as well as others, though its accuracy (72%) is also significantly improved compared with the universal model accuracy (34%). The lower accuracy of the fifth subject can be explained by his P300, the amplitude and latency of which are both quite different from those of other subjects.

D. Discussions

As described above, the proposed EEG classification techniques have a few advantages compared with the traditional supervised EEG classification techniques. First, it removes the tedious and complicated training procedure and makes the BCI systems friendly to end users. Second, the accuracy of the adapted subject model is pretty high and close to the accuracy of the supervised model in most cases as illustrated in Fig. 4.

On the other hand, the proposed techniques also have a few limitations. First, the adapted model is simply trained by EEG and the labels predicted by the universal subject model. An iterative modeling updating procedure should be helpful to derive a better subject model. Second, the proposed techniques are just evaluated by a P300 based word speller. It may be applied to other BCI tasks such as motor imagery. We will study these two issues in our future work.

V. CONCLUSIONS

This paper presents an adaptive electroencephalogram (EEG) classification technique and its applications to a P300 based word speller. First, a universal subject model is built by learning from a pool of subjects, which outperforms the cross-subject models greatly in term of the P300 identification accuracy. Based on the universal subject model, a subject-specific model is then adapted through a

unsupervised learning process. Experiments over ten subjects show that the adapted subject model removes the training procedure and is capable of achieving virtually the same accuracy as supervised subject models.

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