

Unsupervised Brain Computer Interface based on Inter-Subject Information

Shijian Lu, Cuntai Guan, and Haihong Zhang

Abstract—This paper presents an unsupervised subject modeling technique and its application to a P300-based word speller. Due to EEG variations across subjects, a special training procedure is required to learn a subject-specific classification model (SSCM). To deal with the inter-subject variation, we first study a subject independent classification model (SICM) that is learned from EEG of a pool of subjects. Next we further adapt the SICM by learning from a subset of the pooled EEG that is automatically selected based on its similarity to the EEG of a new subject. Experiments over ten healthy subjects show that the SICM learned from all pooled EEG outperforms the cross-subject models greatly. More importantly, the adapted SICM achieves virtually the same performance as the SSCM, hence removing the complicated and tedious training procedure.

I. INTRODUCTION

Brain computer interface (BCI) [1], [2] is a direct communication pathway between a human brain and an external device. As it directly reads electrical signatures of brain's activity and its responses to external stimuli, it is particularly useful for those paralyzed people who suffer from severe neuromuscular disorders and cannot communicate through the normal neuromuscular pathway.

P300 is an endogenous, positive polarity component of the event-related brain potential (ERP) and has been widely used for the purpose of brain computer interface. Farwell and Donchin [3] first demonstrate the use of P300 in a so-called oddball paradigm. In the paradigm, the computer displays a matrix of cells and flashes each row and column shown in Fig. 1 alternately in a random order. A subject trying to input a letter needs to focus on the letter for a short while, meanwhile a P300 ERP will be elicited when the row or the column of the focused letter flashes. The elicited P300 can then be identified by certain signal processing and machine learning algorithms [4], [5].

Many studies [8], [9] have shown that large variations exist among P300 of different subjects. In particular, the P300 amplitude and latency vary among both normal and clinical populations shown in Fig. 2. Consequently, P300 models learned from one subject usually would not apply well to another subject. And most P300-based BCIs require a special training procedure to first build a subject-specific classification model (SSCM). However, the special training procedure is usually complicated and tedious, which makes P300-based BCIs inconvenient for practical uses.

To deal with the EEG variations, we first study a subject-independent classification model (SICM) that is learned from a pool of subjects. Compared with P300 models learned



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

from one specific subject, the SICM learned from a pool of subjects should be more capable of capturing the common P300 characteristics and so has higher potential to classify EEG of a new subject without the special training.

Next, we further study to extract a subset of the pooled EEG that has similar P300 pattern to EEG of a new subject. Particularly, a SSCM is first built based on the EEG segment recorded from the new subject online and the corresponding labels predicted by the SICM (learned from all pooled EEG offline). The pooled EEG is then classified by the newly built SSCM and a subset with high similarity (to EEG of the new subject) is selected based on the SSCM classification confidence. After that, the SICM is rebuilt by learning from the subset of pooled EEG, which is further applied to classify the ensuing EEG of the new subject. Such process iterates until certain amount of EEG of the new subject is classified and incorporated into the SICM adaptation.

II. PROPOSED EEG CLASSIFICATION TECHNIQUES

This section presents our proposed EEG classification technique. In particular, we will divide this section into four subsections, which deal with EEG preprocessing, EEG classification by using linear discriminant, subject-independent EEG classification, and SICM adaptation, respectively.

A. EEG Preprocessing

The collected EEG $E_{c \times s}$ (c and s stand for the number of channels and the number of samples within each channel, respectively) needs to be preprocessed before its classification. In the proposed technique, a low-pass filtering of EEG is first implemented by using an optimal cutoff frequency [6]. The filtered EEG is then down-sampled to reduce the data size and speed up the ensuing processing.

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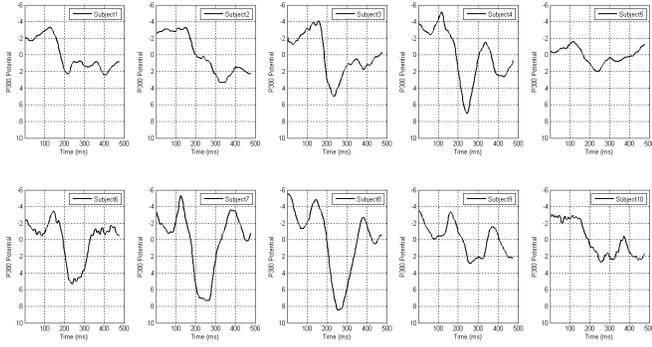


Fig. 2. P300 ERP of ten healthy subjects: P300 is measured at PO6 and averaged over 820 stimulations (41 characters \times 10 rounds \times 2 flashes including one row flash and one column flash that specify the focused cell).

Ocular artifacts are then removed by treating the sampled EEG $E(n)$ as a linear superposition of the measured EOG $u(n)$ and the real EEG $w(n)$. We remove the EOG by using the difference model reported in [5] as follows:

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

where $n' = n - 1$ and N is the number of sites at which the EOG measurement is done, two in our setup. 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. EEG Classification

Under the oddball paradigm, 12 flashes intensify in a random order where one row flash and one column flash specifying the focused cell have P300 and the rest has no P300. Therefore, the EEG classification is actually a two-class classification problem. To facilitate the ensuing EEG classification, we first concatenate the EEG $E_{c \times s}$ collected within an epoch into a feature vector as follows:

$$x = [x(1)^T, \dots, x(i)^T, \dots, x(c)^T]^T \quad (2)$$

where $x(i)$ refers to the EEG collected from the i -th selected channel (composed of s EEG signals sampled between 150 ms and 500 ms after each flash) and the parameter c refers to the number of channels selected (i.e. 8 in our setup).

Different EEG classification techniques have been reported, among which supported vector machine (SVM) and Fisher's linear discriminant (FLD) outperform others as evaluated in [7]. We identify P300 by using FLD because of its lower computational cost. Particularly, FLD seeks to determine a linear combination of the feature vector x that maximizes the ratio of its between-classes variance to its within-classes variance as follows:

$$\operatorname{argmax}_w J(w) = \frac{w^T S_b w}{w^T S_w w} \quad (3)$$

where S_b and S_w correspond to the between-classes scatter matrix and within-classes scatter matrix, respectively.

The quantity $J(w)$ in Equation (3) is well known as the generalized Rayleigh quotient where the projection w can be determined as follows [10]:

$$w = S_w^{-1}(\mu_1 - \mu_2) \quad (4)$$

where μ_1 and μ_2 refer to the mean of the EEG feature vectors with and without P300, respectively. For the two-class classification case, the linear projection w can be similarly derived by the discriminant function that maximizes the posterior probability as follows:

$$g_i(x) = \ln p(\theta_i|x) = \ln p(x|\theta_i) + \ln p(\theta_i), i = 1, 2 \quad (5)$$

where $p(\theta_i), i = 1, 2$ in Equation (5) refers to a priori, which is equal to 1/6 or 5/6, respectively, according to the protocol of the P300-based word speller. The parameters of the $p(x|\theta_i), i = 1, 2$ can be estimated from the converted training feature vector x . P300 can thus be identified by the row and the column that have the maximum P300 posterior probability averaged over multiple rounds of flashing (which are normally required by most P300-based word speller).

C. Subject-Independent EEG Classification

The subject-independent EEG classification is based on the observation that different subjects usually share common characteristics within their P300. Therefore, compared with a P300 model learned from one specific subject, a SICM learned from a pool of subjects should be more capable of capturing the common P300 characteristics and classifying EEG of a new subject without the special training.

To build a subject-independent model, EEG of a pool of subjects specified below is required:

$$X = \left\{ [x_{s1}^T, l_{s1}], \dots, [x_{si}^T, l_{si}], \dots, [x_{sn}^T, l_{sn}] \right\} \quad (6)$$

where x_{si} and l_{si} refer to the feature vectors converted from EEG of the i -th subject and the corresponding labels, respectively. With the X , the Gaussian distribution $p(x|\theta_i)$ in Equation (5) can be estimated and a SICM can then be built. Experiments (to be discussed in Section III) show that the SICM outperforms the cross-subject models greatly.

D. Subject-Independent Model Adaptation

Though the SICM described in the last subsection is capable of identifying P300 of a new subject with no special training, the classification accuracy is normally much lower than the SSCM accuracy. The low accuracy can be explained by the fact that the SICM captures the common instead of the subject-specific P300 characteristics.

We capture subject-specific EEG characteristics through the selection of a subset of the pooled EEG that has similar P300 pattern as that of a new subject. Algorithm I below describes the online SICM adaptation process step by step:

Algorithm I

Input: Labeled EEG E from a pool of subjects and a new subject to be studied.

Step 1: Preprocess E and convert it into a training set X as specified in Equation (6).

Step 2: Build a SICM by learning from the X .

Step 3: Preprocess and convert the initial EEG segment of the new subject (recorded online) into feature vectors x_1 . Then classify x_1 by using the SICM built in Step 2.

Step 4: Build a SSCM based on the x_1 and the corresponding labels l_1 that are predicted by the SICM in Step 3.

Step 5: Classify the X by using the SSCM inversely and determine a subset of X that has similar P300 pattern to that of the x_1 (based on the SSCM classification confidence). Rebuild the SICM by learning from the subset of X .

Step 6: Preprocess and convert the ensuing EEG segments of the new subject into feature vectors x_i . Then classify the subject EEG $x_1 \cdots x_i$ by using the rebuilt SICM.

Step 7: Rebuild the SSCM by using all subject EEG x_1, \dots, x_i and the corresponding labels predicted by the SICM.

Step 8: Repeat Steps 5-7 until the certain amount of EEG of the new subject has been classified.

In the proposed technique, the similarity between EEG of the new subject and pooled EEG is measured by the confidence of the SSCM when it is applied to classify the pooled EEG inversely. Besides, the SSCM confidence is evaluated based on the classification consistency as follows:

$$C_i = P\left(\sum_{j=1}^R \text{MAX}(\Phi_j)\right) - SP\left(\sum_{j=1}^R \text{MAX}(\Phi_j)\right) \quad (7)$$

where R is the number of the rounds for the spelling of a character and Φ_j is a 12-dimensional vector storing the P300 probability of the 12 flashing within j -th round. The function $\text{MAX}()$ returns a 12-dimensional vector, which sets the row and the column with the maximum P300 posterior probability at 1 and the rest at 0. The functions $P()/SP()$ return the sum of the frequency of the peak/second-peak row and column accumulated over R rounds of stimulation.

The evaluation of the confidence by the classification consistency is based on the observation that EEG with P300 usually shows specific P300 pattern but those without P300 is much more random. Therefore, if a model identifies one specific row/column more consistently over multiple rounds of stimulation and the frequency of the peak row/column is much higher than that of the second-peak row/column, the model should be more confident. In our implemented system, the subset of the pooled EEG is selected as the first 50% most confident among those correctly classified by the SSCM.

III. EXPERIMENTAL RESULTS

We evaluate the proposed technique based on EEG collected from ten healthy subjects. Particularly, two EEG sessions are collected from each subject by spelling 41 characters [5] (THE QUICK BROWN FOX JUMPS OVER LAZY DOG 246138 579) in two different orders. Ten rounds of flashes are implemented for the spelling of each character and within each epoch, EEG between 150 ms and 500 ms after each flash are used for the EEG classification. In addition, we select 8 channels (Fz Cz P3 Pz P4 PO7 PO8 OZ) and set the sampling rate at 250.

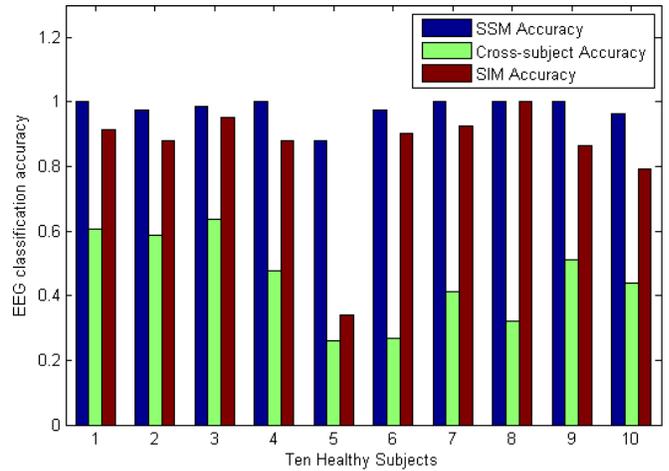


Fig. 3. Accuracy of SSCMs (blue bars on the left), pooled SICMs (green bars in the middle), and cross-subject models (red bars on the right).

A. P300 Variability

We study the P300 variability through the comparison of the subject-specific and cross-subject EEG classification. Ten SSCMs are first built by learning from the first EEG session (or the second EEG session for two-fold cross validation) of the ten subjects. The ten subject models are then applied to classify the second EEG session of the ten subjects, respectively. The blue and green bars in Fig. 3 show the SSCM accuracy and the cross-subject model accuracy averaged over the nine cross-subject models (learned from the other nine subjects). Obviously, the cross-subject accuracy is significantly lower than the SSCM accuracy, indicating the EEG variations across subjects.

B. Subject-Independent EEG Classification

The subject-independent EEG classification has also been tested. Particularly, for each of the ten healthy subjects, a SICM is first built by learning from the first EEG session of the other nine subjects (or the second session for two-fold cross validation). The SICM is then applied to classify second EEG session of the i -th subject under study.

The red bar in Fig. 3 shows the SICM accuracy. As Fig. 3 shows, the SICM accuracy is generally much higher than the cross-subject accuracy. Such results indicate that the combination of EEG of a pool of subjects does improve the EEG classification greatly. On the other hand, the SICM accuracy is still lower than the SSCM accuracy, which concurrently indicates the limitation of the SICM, i.e. it does not capture the subject-specific P300 characteristics.

C. Subject-Independent Model Adaptation

The proposed SICM adaptation technique has been evaluated as well. To show the effectiveness of the proposed technique, we simply test one iteration of the SICM rebuilding as described in Algorithm I. Particularly, one EEG session of each of the ten subjects is first classified by the pooled SICM learned from EEG of the other nine subjects. A SSCM is then built and applied to classify pooled EEG of the other

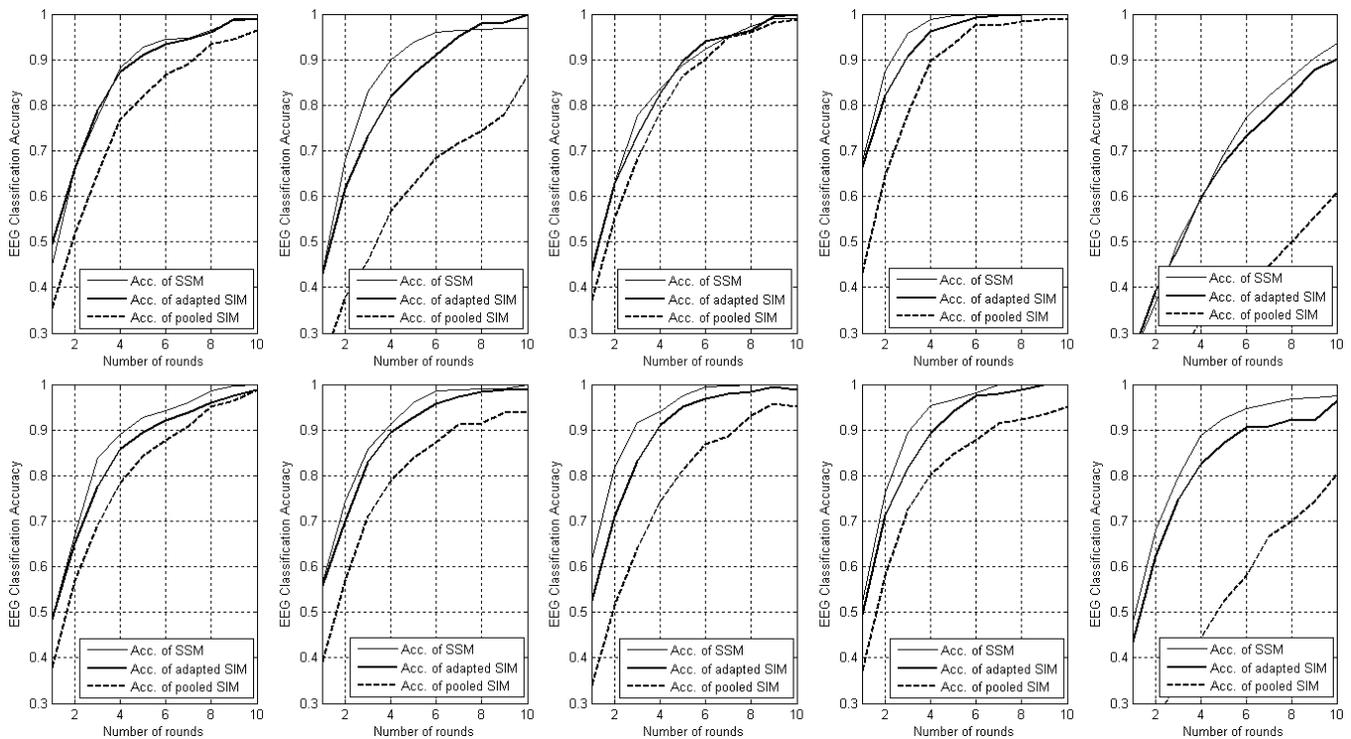


Fig. 4. Accuracy of the pooled SICMs (dashed graph), SSCMs (solid light dark graph) and adapted SICMs (solid heavy dark graph).

nine subjects inversely. A subset of the pooled EEG is then selected as described in Section II. D to rebuild the SICM, which is further applied to classify the other EEG session of the subject under study for the accuracy evaluation.

Fig. 4 shows the two-fold cross validation accuracy of the pooled SICMs (learned from all pooled EEG), adapted SICMs, and the SSCMs when the round number increase from 1 to 10. As Fig. 4 shows, both the SSCMs and the adapted SICMs significantly outperform the pooled SICM (except for the third subject whose SSCM accuracy and SICM accuracy are rough the same). At the same time, the accuracy of the adapted SICM is very close to that of the SSCM, indicating its potential to remove the complicated and tedious training procedure.

Several issues need to be further investigated. First, the proposed technique is tested over ten healthy adult subjects. But for subjects of different categories such as children and patients, larger P300 variation can be expected, which may affect the performance of the proposed technique. Second, the proposed technique is just tested over a P300-based word speller. But it has potential to be applied to other more challenging BCI tasks such as motor imagery. We will study these two issues in our future work.

IV. CONCLUSIONS

This paper presents an unsupervised EEG classification technique and its application to a P300-based word speller. In the proposed technique, a SICM is first learned from EEG of a pool of subject. Next, the SICM is recursively updated by learning from those pooled EEG with high similarity to

the EEG of the new subject. Experiments over ten healthy subjects show that the adapted SICM is capable of achieving virtually the same performance as the SSCM, hence removing the complicated and tedious training procedure.

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