Subject-Independent Brain Computer Interface through Boosting

Shijian Lu, Cuntai Guan, and Haihong Zhang
Institute for Infocomm Research 1, Fusionopolis Way, #21-01 Connexis
Singapore 138632
slu,ctguan,hhzhang@i2r.a-star.edu.sg

Abstract

This paper presents a subject-independent EEG (Electroencephalogram) classification technique and its application to a P300-based word speller. Due to EEG variations across subjects, a user calibration procedure is usually required to build a subject-specific classification model (SSCM). We remove the user calibration through the boosting of a committee of weak classifiers learned from EEG of a pool of subjects. In particular, we ensemble the weak classifiers based on their confidence that is evaluated according to the classification consistency. Experiments over ten subjects show that the proposed technique greatly outperforms the supervised classification models, hence making P300-based BCIs more convenient for practical uses.

1 Introduction

The emerging technology of brain-computer interface (BCI) has attracted increasing interest from multidisciplinary domains [1]. The technology directly translates brain signals into communication messages while bypassing normal neuromuscular pathways. Thus it potentially provides severely paralyzed people with communication, control or rehabilitation tools to help compensate or restore their lost capabilities.

P300 is an endogenous, positive polarity component of the event-related brain potential (ERP) and it has been widely used for the purpose of brain computer interface (BCI). Farwell and Donchin [2] 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. Subjects needs to focus on a cell for a short while, meanwhile a P300 ERP will be elicited in the subject's EEG (Electroencephalogram) when the row or the column specifying the focused cell flashes. The elicited P300 can then be identified by signal processing and machine learning algorithms [3, 4].

Figure 1. Interface of P300-based speller.

Many studies [7, 8] have shown variations of P300 across subjects. In particular, P300 amplitude and latency vary among both normal and clinical populations shown in Fig. 2. As a result, P300 models learned from one subject would not apply well to another subject. To deal with such EEG variations, most P300-based BCIs usually perform a user calibration to build a subject-specific classification model (SSCM). But the user calibration makes BCIs inconvenient for practical uses.

This paper presents a subject-independent EEG classification technique that does not require the user calibration. The proposed technique is based on the observation that P300 of different subjects usually share common waveform characteristics as defined, namely, a positive peak after around 300 ms of the external stimuli. It directly classifies EEG a new subject by boosting multiple weak EEG classifiers that are learned from EEG of a pool of existing subjects.

2 Proposed Techniques

This section presents our proposed EEG classification technique including the EEG preprocessing, the EEG classification by using linear discriminant, and the boosting classification, respectively.

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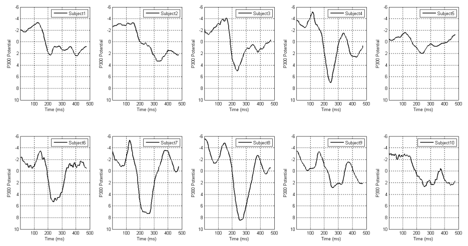

Figure 2. P300 of ten healthy subjects.

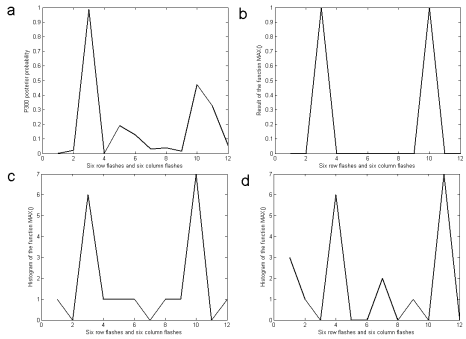

Figure 3. (a) P300 posterior probability of the 12 flashes within one round; (b) Results of MAX(); (c) Histogram of MAX() over 10 rounds; (d) Histogram of MAX() over another 10 rounds.

2.1 EEG Preprocessing

Collected EEG needs to be preprocessed. In the proposed technique epoched EEG is frst fed into a low-pass filter and then down-sampled at 60Hz. A ten-order Chebyshev II type IIR filter is then implemented where the passband cut-off frequency is set at 10Hz [5].

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 the difference model [4] 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 is measured, two in our setup.

2.2 EEG Classification

Before the EEG classification, we first convert the each epoched EEG into a feature vector as follows:

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

where $x(i)$ refers to the EEG collected from the i-th selected channel and the parameter c refers to the number of channels selected (8 in our setup).

Different EEG classification techniques have been reported [6]. We identify P300 by using Fisher's linear discriminant (FLD), which determines a linear combination of a feature vector that maximizes the ratio of its between-classes variance to its within-classes variance:

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

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

For the two-class classification, the linear combination w can be similarly derived by the discriminant function that maximizes the posterior probability:

$$\phi_i(x) = \ln p(\theta_i|x) = \ln p(x|\theta_i) + \ln p(\theta_i), i = 1,2 \quad (4)$$

where $p(\theta_i), i = 1,2$ refers to a priori, which is equal to 1/6 or 5/6 according to the protocol of the P300-based word speller. The $p(x|\theta_i), i = 1,2$ has a Gaussian distribution and its parameters can be estimated from training EEG. P300 can thus be identified by the row/column that has the maximum P300 posterior probability averaged over multiple rounds of stimulation.

2.3 Boosting Classification

This section presents the proposed boosting technique. First, a committee of weak classifiers is built by learning from EEG of a pool of subjects. Multiple weak classifiers are then weighted according to their confidence. Particularly, we measure the classifier confidence based on the classifier consistency evaluated over multiple rounds of stimuli:

$$C_i = P(\sum_{j=1}^{R} MAX(\Phi_j)) - SP(\sum_{j=1}^{R} MAX(\Phi_j)) \quad (5)$$

where R is the number of the rounds and Φ_j is a 12-dimensional vector storing the P300 posterior probability of the 12 flashes within the j-th round. $MAX()$ is defined as follows:

$$MAX(\Phi_j) = \begin{cases} 1 & \text{the row/column with the peak Pdf} \\ 0 & \text{others} \end{cases} \quad (6)$$

The functions $P()/SP()$ return the sum of the frequency of the peak/second-peak row and column accumulated over R rounds of flashing, respectively.

Fig. 3 illustrates the measurement of the classifier confidence. For one specific EEG classifier, Fig. 3a

Table 1. Accuracy of SSCMs and and cross-subject classification models.

Testing EEG / Training EEG	Subject1	Subject2	Subject3	Subject4	Subject5	Subject6	Subject7	Subject8	Subject9	Subject10
Subject1	0.9878	0.8049	0.9268	0.8659	0.4146	0.8293	0.7195	0.6951	0.8537	0.4756
Subject2	0.9024	0.9756	0.8293	0.5854	0.2927	0.4756	0.3659	0.4024	0.8415	0.4268
Subject3	0.9146	0.7317	0.9878	0.8537	0.2561	0.8415	0.6341	0.7073	0.6829	0.6341
Subject4	0.7805	0.4634	0.7683	1.0000	0.4024	0.8902	0.5976	0.4878	0.8780	0.3659
Subject5	0.4878	0.2805	0.5000	0.6341	0.9024	0.6829	0.5244	0.6707	0.4024	0.1707
Subject6	0.5854	0.1463	0.6585	0.8659	0.4024	1.0000	0.9512	0.9634	0.6829	0.1951
Subject7	0.5488	0.2805	0.6585	0.8780	0.3659	0.8537	1.0000	0.8780	0.6585	0.2317
Subject8	0.2439	0.2073	0.4390	0.5000	0.1098	0.8902	0.6585	1.0000	0.2073	0.3049
Subject9	0.8902	0.8902	0.9024	0.9878	0.5366	0.9268	0.8293	0.8171	1.0000	0.5244
Subject10	0.8415	0.6220	0.7195	0.5244	0.1463	0.5366	0.6220	0.7805	0.5610	0.9512

shows the P300 posterior probability of the 12 flashes within one round. Fig. 3b shows the results of the function $MAX()$ in Equation (5). Fig. 3c further shows the peak row/column accumulated over 10 rounds of flashing. As we can see, the frequency of the peak row/column (i.e. 3rd row and the 4th column) reaches up to 6 and 7, respectively. Thus the two functions $P()$ and $SP()$ in Equation (5) return 13 (i.e. $6+7$) and 2 (i.e. $1+1$), respectively. The classifier confidence can be finally evaluated at 11 (i.e. $13-2$).

The confidence measurement is based on the fact that EEG with P300 usually shows specific P300 pattern but those without P300 is much more random. Clearly, the classifier consistency is high when 1) the frequency of the peak row/column is high; 2) the frequency difference between the peak and the second peak row/column is high. The second condition ensures the saliency of the frequency of the peak row/column. As Fig. 3d shows, though the frequency of the peak row/column of another ten rounds of flashing is the same as that in Fig. 3c, the confidence is just 8 (i.e. $13-5$).

The weak classifiers can thus be combined based on their confidence. Particularly, the posterior probability of the boosted classifier is derived by weighting the posterior probability of multiple weak classifiers:

$$\Phi = \frac{\sum_{i=1}^{N} C_i \cdot \Phi_i}{\sum_{i=1}^{N} C_i} \tag{7}$$

where N is the number of weak classifiers and Φ_i is the same as defined in Equation (5). C_i refers to the confidence of i-th subject.

3 Experimental Results

We evaluate the proposed technique by EEG collected from ten healthy subjects. For each subject, two EEG sessions are collected by spelling 41 characters (THE QUICK BROWN FOX JUMPS OVER LAZY DOG 246138 579) in two different orders. Ten rounds of flashing are implemented for the spelling of each character and EEG between 150 ms and 500 ms following each flash is recorded. Besides, EEG is recorded by using eight channels (Fz Cz P3 Pz P4 PO7 PO8 OZ) with sampling rate at 250Hz.

3.1 P300 Variability

We study the P300 variability through the examination of the cross-subject EEG classification. First, ten FLD classifiers are built by learning from the first EEG session (or the second session depending on two-fold cross validation) of the ten subjects. After that, the ten classifiers are applied to classify the second EEG session of the ten subjects, respectively. Table I shows the accuracy of the subject-specific (diagonal items) and cross-subject (non-diagonal items) classifiers. Obviously, the cross-subject accuracy is significantly lower than the subject-specific accuracy, indicating the EEG variation across subjects.

3.2 Boosting Classification Technique

The proposed technique has also been tested. First, ten classifiers are built as described in the last subsection. The boosted classifier accuracy for each subject is then evaluated by weighting the nine weak classifiers learned from EEG of the other nine subjects.

The solid and dashed graphs in Fig. 4 show the accuracy of the subject-specific and the boosted classifiers when the round number is increased from 1 to 10. As Fig. 4 shows, the boosted classifier greatly outperforms the subject-specific classifiers when the round number is small. Besides, the boosted classifier achieves roughly the same accuracy as the subject-specific classifiers at the tenth round, indicating its potential to remove the complicated and tedious training procedure. The higher accuracy of the boosted classifer

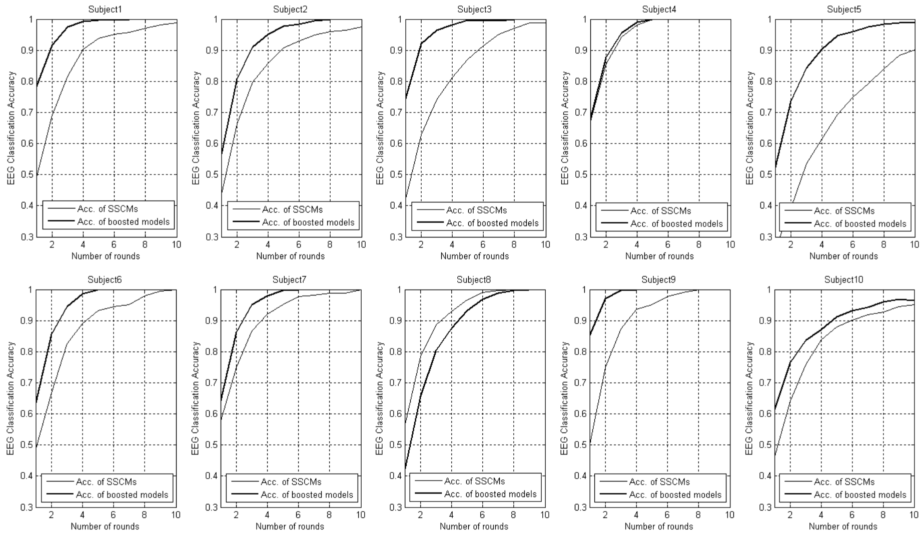

Figure 4. Accuracy of SSCMs and boosted classification models.

(at the lower number of round) can be explained by the heavy noise, which is suppressed by the boosted classifier through the weighting of multiple weak classifiers.

4 Conclusions

This paper presents a subject-independent EEG classification technique that boosts a committee of week classifiers learned from EEG of a pool subjects. The proposed technique weights the weak classifiers based on their classification confidence. Experiments over ten subjects show that the proposed technique even outperforms the subject-specific classifiers, hence removing the complicated and tedious training procedure.

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