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An Effective BCI Speller Based on Semi-supervised Learning

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Abstract— **Brain-computer interfaces (BCIs) aim to provide an alternative channel for paralyzed patients to communicate with external world. Reducing the time needed for the initial calibration is one important objective in P300 based BCI research. In this paper, the training time is reduced by a semi-supervised learning approach. A model is trained by small training set first. The on-line test data with predicted labels are then added to the initial training data to extend the training data. And the model is updated online using the extended training set. The method is tested by a data set of P300 based word speller. The experimental results show that 93.4% of the training time for this data set can be reduced by the proposed method while keeping satisfactory accuracy rate. This semi-supervised learning approach is applied on-line to obtain robust and adaptive model for P300 based speller with small training set, which is believed to be very essential to improve the feasibility of the P300 based BCI.**

I. Introduction

Brain-computer interfaces (BCIs) provide an alternative communication and control channels to convey messages and commands from brain to the external world [1]. It is almost the only way for locked-in patients (paralyzed patients that unable to control any muscle) to send their commands to computer controlled devices. Currently, EEG is the most prevailing signals of brainwave for non-invasive BCIs. One strategy of EEG based BCI is realized by event related potential that exploits the electrophysiological responses to a certain event. This strategy belongs to the independent BCIs [1], as it is not dependent on the activity from peripheral nerves or muscles. The most robust feature of the event related potential is a positive displacement occurring around 300ms after stimulus, which is known as the P300 or P3 [2].

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P300 was first applied in BCI as a speller by Farwell and Donchin in [3]. There are other applications such as image triage of rapid serial visual presentation [4]. The main issue of P300-based BCI is to classify the P300 response and the background noise robustly. Many research interests have been attracted to improve the performance of the P300 based speller. Promising accuracy was reported by different research groups (90% in [5] and 92.1% in [6]). In feature extraction, independent component analysis [6-7] and continuous Wavelet transform with t-statistics [8] were applied. Genetic algorithm was employed in the feature selection and classification of P300 signals [9]. In the aspect of classification, the variability of P300 response within a subject was considered in [10]. A statistical model was proposed in [11] to reject the undesired signals. Perceptual characteristics of neighbor stimuli of the targets were studied to improve the performance of the speller in [12]. Support vector machine (SVM) is the most popular classification method applied in the P300 based speller [10-13]. However, training time is relatively long for P300 based BCI, which will hinder the system to attract more users.

One important objective in BCI research is to reduce the time needed for the initial calibration. Not only P300 based BCIs, other BCIs such as motor-imagery also have the similar challenge. For example, Berlin BCI group provides a motor-imagery data set for the BCI competition 2005 with only a little amount of training data [14 -15]. The approach they proposed is to use information from other subjects' measurements to reduce the amount of training data needed for a new subject. A novel semi-supervised learning algorithm, EM algorithm embedded with feature re-extraction, was presented in [16] by our group to reduce the training time of motor imaginary-based BCI systems. The semi-supervised learning is efficient for motor imaginary, so we want to extend the method to P300 speller here. Under supervised learning, we investigated how to optimize the training process of P300 based speller by studying the dependence of accuracy on the number of visual stimuli, P300 segment length used, the number of channel used and the amount of training data used [17]. We want to further improve the efficiency of the training process by semi-supervised learning here.

A semi-supervised SVM is employed in this paper to train a robust P300 model from small training set. The online test data with predicted labels are combined to the initial training set to obtain a robust model for each subject. The details of the algorithm are described in section II. Experimental results of a dataset from P300 based speller is shown in section III. Section IV gives a concise conclusion of this paper.

II. METHODOLOGY

A. SVM and semi-supervised SVM

SVM is a classification method that constructs an optimal hyperplane with the largest separation margin between two classes. Given a training set with N samples, a standard SVM classifier with linear kernel for two classes can be described as the following optimization problem:

$$\min \quad f(w,\xi)=\frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i \qquad (1)$$

Subject to

$$y_i\,(w^T x_i + b) \ge 1-\xi_i\,, \quad \xi_i \ge 0,\ i=1,\ldots,N. \qquad (2)$$

where $x_i \in R^n$ is a training feature vector, $y_i \in \{-1,1\}$ is the corresponding class label. C > 0 is regularization constant. b is an offset value, and ξ_i is the slack-variable for pattern x_i.

For the test data, the class label of a new vector x can be predicted by projecting it on the weight vector w:

$$g(x)=w^T x + b \qquad (3)$$

The predicted label is decided by the sign of this projection.

A semi-supervised SVM is applied to solve the classification problem with small training set here. The unlabelled data with the predicted labels are added to the initial training set to retrain the classifier. The details of the semi-supervised SVM are described as the following three steps:

Initial step: For the initial training set of N_1 samples with labels, a SVM classifier is trained according to Equation (1). The optimized parameters are represented as $w^0 \in R^n$, $\xi^0 \in R^{N_1}$, and b^0. The predicted labels for the test data set of N_2 samples are denoted as $[y^0(N_1+1),\ldots,y^0(N_1+N_2)]$.

Retrain step: The samples in the test data set with predicted labels are added to the initial training set. The SVM classifier is retrained based on the extended training set. In the kth iteration, the optimized parameter is denoted as $w^k \in R^n$, $\xi^k \in R^{N_1+N_2}$, and b^k. $[y^k(N_1+1),\ldots,y^k(N_1+N_2)]$ stands for the predicted labels in the kth iteration.

Termination step: Compare the predicted labels in the kth iteration and (k-1)th iteration. The termination condition is that the number of the label change is less than a predefined value. The predicted labels in the kth iteration $[y^k(N_1+1),\ldots,y^k(N_1+N_2)]$ are the final class labels if the termination condition is satisfied, otherwise (k+1)th iteration needs to perform until the termination condition is met.

B. Semi-supervised SVM applied to P300 Speller

The P300-based speller paradigm was implemented as described in [5]. A six by six matrix that includes characters and numbers is presented to the users on a computer screen (refer to Fig. 1). The rows and columns of the matrix are intensified successively in a random order. Each intensification lasts for 100 ms followed by a 75 ms break. The user focuses on the character or number that he wishes to communicate and counts the number of times the row and the column of the chosen symbol are intensified. An event related potential was elicited in response to the counting. Two of twelve consecutive intensifications in each run contain the chosen symbol, which will generate P300 response. For each symbol, ten runs of twelve intensifications are shown on the screen.

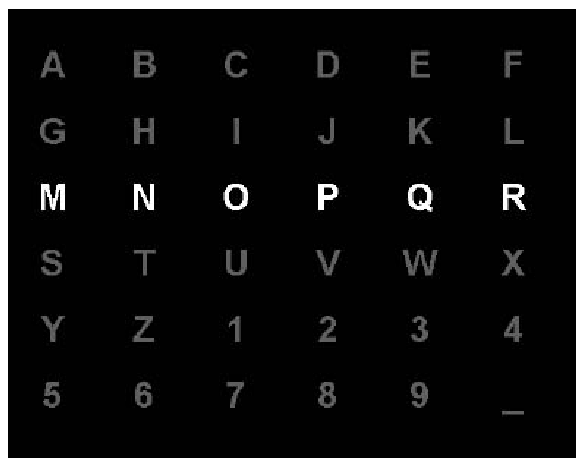

Fig.1 The stimulus matrix shown to the user. One of the rows or one of the columns of the matrix was intensified.

Traditionally, the training set consists of a large number of training samples to train a robust model for each subject. Thus a relatively long preparation time is needed before the P300 based speller can be used by the subject, which is tiresome for the user. The semi-supervised SVM described in section II.A is applied to P300 based speller. This is a two-class problem: P300 response and background noise. A SVM model is first trained based on the small training set. Then the SVM model is updated based on the initial training set together with the test data with predicted labels. Small amount of training samples is needed for initial training so that training time is reduced. Extend the initial training set by the test data with predicted labels, the amount of training samples is sufficient to train a robust model. Experimental results of P300 based speller will be shown in the next section to demonstrate the effectiveness of our approach.

III. RESULTS AND DISCUSSION

The experimental data were obtained from a P300 based speller. Two data sets were collected from ten subjects for two-fold cross validation. The 41 character phrase "THE QUICK BROWN FOX JUMPS OVER LAZY DOG 24613 8579" was used for both data set collection with different word order. The sampling rate is 250Hz.

In the original work [17], training data contains all of the 41 symbols. The data segments between 150ms and 500 ms of 24 channels after low pass filtering were selected as the feature. The average accuracy of the ten subjects for two fold cross validation is shown in Fig. 2 when all of the 41 characters in the training set are employed to train the model by the standard SVM method.

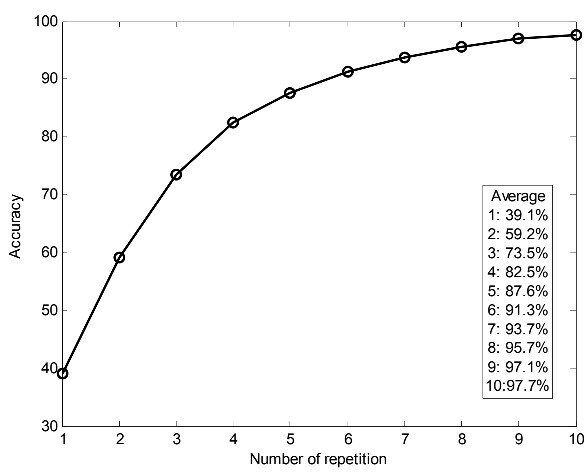

Fig.2 Cross-validation result when all of the 41 characters in the training set are used to train the SVM model. It is the average accuracy of ten subjects.

In order to reduce the training time, here only 3 symbols in the training data are employed as the initial training set. The other 38 symbols are used to retrain the model using their predicted labels. Semi-supervised learning approach introduced in section II was applied. To simplify the problem, 10 more characters from the training set are added to extend the initial training set in each retrain. So four times of retrain are performed and the last 8 characters are added in the last retrain. The average accuracy improvement with nine runs of repetition for the two-fold cross validation is demonstrated in Fig. 3, where the circles indicate the beginning of a retrain. It can be observed from the figure that an absolute 17.5% (97.0-79.5=17.5) of accuracy improvement or a relative 22.0% ($\frac{97.0-79.5}{79.5}\times 100\% = 22.0\%$) of accuracy improvement is obtained, which shows the effectiveness of the semi-supervised SVM. In the real-time system, the model can be updated with each test character added to the training data.

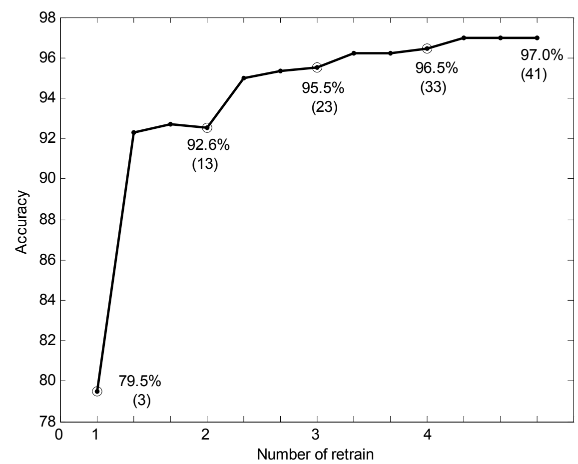

Fig.3 Average accuracy improvement by semi-supervised SVM with repetition of nine ('o'—beginning of a retrain; '.'—iteration in a retrain, the number in parentheses indicates the number of training characters).

The experimental results are shown in table 1. The accuracy of the two-fold cross validation and training set label prediction are both presented in the table. From table 1, we can see that the semi-supervised SVM method can achieve much better accuracy than standard SVM for both two-fold cross validation and training set label prediction when initial training data set is small. Using only 3 characters as the initial training set, semi-supervised SVM can achieve comparable accuracy (97.6%) with the standard SVM using all of the 41 training characters (97.7%) under the condition that all the ten repetition is used. Thus 92.7% ($\frac{41-3}{41}\times 100\% = 92.7\%$) of the training time is reduced while accuracy is kept. It can also be noted from the table that the repetition of each character can be reduced at the same time from ten to nine while keeping the satisfactory accuracy (accuracy reduction from 97.7% to 97.0%). In this case, we can reduce 93.4% ($\frac{41\times 10-3\times 9}{41\times 10}\times 100\% = 93.4\%$) of the training time, which is very essential to improve the usability of P300-based speller.

Table 1 Accuracy for P300-based speller dataset with initial training set of 3 characters

Number of Repetition	Training set label prediction		Two-fold cross-validation	
	Standard SVM	Semi-supervised SVM	Standard SVM	Semi-supervised SVM
5	53.6%	81.0%	55.3%	81.3%
6	64.2%	85.7%	63.2%	88.9%
7	70.52%	92.2%	66.7%	93.4%
8	76.7%	96.0%	74.9%	95.6%
9	82.1%	96.6%	79.5%	97.0%
10	84.2%	97.4%	81.3%	97.6%

IV. CONCLUSION

In this paper, a semi-supervised SVM is applied to reduce the training time of P300 based speller. After initial training using small training set, the on-line test data with predicted labels are added to the initial training set to get robust models. The model is updated using the on-line test data. Experimental results from ten subjects show that average 93.4% of the training time for the data set can be reduced by the proposed method. This semi-supervised learning approach can be applied to the real-time P300 speller system to reduce the training time, which can make the P300 based speller more feasible to use.

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