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RESEARCH ARTICLE

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Single-trial EEG classification using in-phase average for brain-computer interface

Abstract Communication signals should be estimated by a single trial in a brain-computer interface. Since the relativity of visual evoked potentials from different sites should be stronger than those of the spontaneous electroencephalogram (EEG), this paper adopted the time-lock averaged signals from multi-channels as features. 200 trials of EEG recordings evoked by target or non-target stimuli were classified by the support vector machine (SVM). Results show that a classification accuracy of higher than 97% can be obtained by merely using the 250–550 ms time section of the averaged signals with channel Cz and Pz as features. It suggests that a possible approach to boost communication speed and simplify the designation of the brain-computer interface (BCI) system is worthy of an attempt in this way.

Keywords in-phase average, visual evoked potentials, brain-computer interfaces, single-trial estimation

1 Introduction

The newly developed brain-computer interfaces (BCIs) are novel human-machine interaction modalities. Different from the traditional modes of interaction with the outside world using peripheral neuromuscular actions (such as sound, emotion or extremity motion, etc.), BCIs exploit specifically selected brain waves (i.e., electroencephalogram, EEG) to communicate directly with computers. They provide alternative approaches for those with disabled bodies to interact within their circumstances. The unique technologies have been extended in wide applications in areas such as controlling aircraft, training, and games [1].

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Currently, several laboratory BCI systems have been successfully developed. Among them there are also several experimental virtual keyboards for a mental speller [2,3]. However, there still exist some deficiencies with the experiments. The main problem of the current BCI is the low communication speed between the user and the computer, such as a low information transfer rate of 30 bit/min [1]. Furthermore, the fatigue caused by the low frequency flashing was another problem. To remedy the deficiencies described above, we construct a BCI-based mental speller exploiting the imitating-natural-reading (INR) inducing paradigm [4] under the support of the National Natural Science Foundation of China.

One of the key issues in constructing a BCI system is precisely conducting the single trial estimation of featured components from recorded EEG. To fulfill a control of the computer, one should first construct feature spaces using a varied form of EEG signals from multi-channels and subsequently utilizing suitable pattern classification algorithms to classify the features and therefore output instructions to the computer [5]. In the present work, the features were enhanced by in-phase average of EEG from multi-channels, and satisfactory single trial classification rate gained by inputting the enhanced features into a classifier of SVM.

2 Experiment

2.1 Data acquisition and preprocessing

The experimental model and data come from the cognitive science laboratory in South-Central University for Nationalities of China. The experiment was set to record EEG signals during target or non-target stimulus onset under the INR paradigm. The INR paradigm is one of the methods of obtaining visual event-related potentials (VERPs) from smoothly presented string-like stimulus, just as a person obtaining information through reading sentences in a textbook. Unlike the usual reading (in which the reader's line of sight moves through sentences), the symbol string (constructed by non-target symbols and one target symbol) moves relative to the "reader" in INR while keeping the reader's line of sight fixated. One's task is to pick out the target symbol from the string, and then VERPs are elicited and embedded in the subject's EEG. Since the eye light is fixated, the contamination of EEG by an electro-oculogram (EOG) could be limited in the maximum by the trick.

Eight healthy male college students participated voluntarily in the experiments. In each trial, the acquisition of EEG started at 210 ms pre-target stimuli and halted at 990 ms post-target stimuli at a sampling rate of 427 Hz. The signal was bandpass filtered between 0.1–45 Hz, thus 512 samples in 1.2 s were sampled totally in every trial. Four EEG electrodes were placed onto standard locations of Fz, Cz, Pz, and Oz according to the 10–20 international system with reference to two earlobe electrodes. More detailed description about the experiment could be found in Ref. [4]. The 512 samples were initially recorded as a 14-KB text-format file for every trial. For convenient processing, the text files were converted through programming into M files of Matlab 6. The format of M files takes the form of: channels by samples by trials. Before construction of feature spaces, classification and validation, several preprocessing operations were applied to the data in the order stated below.

1) Filtering: a ninth-order Butterworth zero-phase forward and reverse digital filter (Matlab function filtfilt) was used for filtering the data. Cut-off frequencies were set to 0 Hz and 10 Hz.

2) Baseline removing: the channel baseline was removed via subtraction of 300 ms-section pre-stimuli from all testing sections.

3) Down sampling: to reduce the dimensionality of feature space, the EEG was down sampled from 427 Hz to 53 Hz by selecting each 8th sample from the lowpass filtered data.

4) Rejecting: eye blinks, eye movement, muscle activity or subject movement can cause large amplitude outliers in the EEG. This is harmful in training classifiers. To reduce the effects of such outliers, records with amplitude of data from any electrode exceeding 45 μV were discarded. Consequently, taking the subject *T* into account, 400 selected trials containing 200 target and 200 non-target signals were ultimately obtained for test from 406 raw trials.

5) Normalizing: the samples (matrix InputMat) from each electrode were normalized using flowing Matlab codes:

```
% Normalize the columns of matrix InputMat
Norm2 = sqrt(diag(InputMat'*InputMat));
Normalized = InputMat./(ones(size(InputMat,1),1)
        *Norm2');
```

2.2 Classification of EEG

In our experiments, the OSU SVM Classifier Matlab Toolbox was used to perform the classification of EEG signals from target stimuli and non-target stimuli. The radial basis function

$$K(x,x_i) = \exp\left(-\gamma\|x-x_i\|^2\right)$$

was taken as kernel function. Details of the algorithm implemented in LIBSVM can be found in Ref. [6].

Based on the similarity of results for all subjects, we present here only the experiment processes and results of a subject T. The testing steps for every trial were as follows:

Step 1 Conduct in-phase average among selected channels.

Step 2 Extract 300 ms section from the averaged signals as features.

Step 3 Input the features into the trained SVM classifier to get a classification of target or non-target signals.

Signals from channel Fz were excluded from all combinations of test. The reasons can be explained by Fig. 1. It shows that the P3 components display instability among varied trials, i.e., they are always "absent" from signals of target stimulated trials. In consequence, this directly results in the low classification rates through using features from only a single channel of Fz.

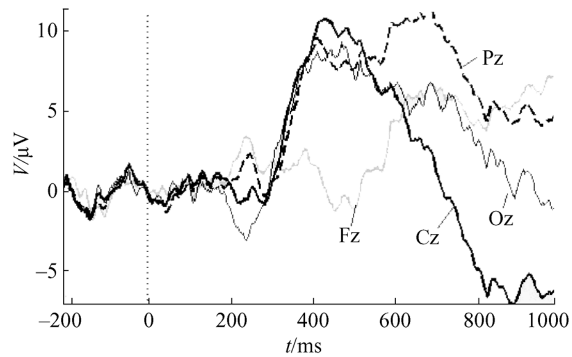

Fig. 1 Averaged evoked potentials waveform of multi-trials from subject T in channel Fz, Cz, Pz, and Oz

At around 240 ms, there are relatively low amplitude P2 components in channel Pz, but P2 is not significant in channel Cz. As for channel Oz, N2 component was found at this moment. It is obvious that the P2 or N2 components would be weakened after in-phase averaging in these channels, which is harmful for single trial classification of these signals. Meanwhile, we noticed that the amplitudes of P3 components in all the three channels were relatively significant, and they reached the maximum within an interval of about 350–500 ms. Thus we are sufficed to expect that P3 components would be enhanced while the stochastic noises would be weakened. Unfortunately, another negative factor of the average is that the coherent spontaneous endogenous EEG would be enhanced simultaneously.

To prevent underestimating the generalization error by over fitting during the training, the dataset of all trials was equally divided into two parts: the training set and testing set. Each set consisted of half trials of target stimuli and non-target stimuli respectively. The parameters of ν-SVM and the generalization error were estimated by a 10-fold cross-validation procedure which was only performed on the training set. Then, with recourse to these best parameters, we performed a leave-one-out procedure 10 times to evaluate the average classification rate on the testing set.

3 Results and discussion

Using the methods described above, various channel in-phase average combinations and time interval selections as features of the classifier are investigated systematically. The signal of 200 target stimuli and 200 non-target stimuli of subject T were equally divided into two groups: training set and testing set, wherein each has 100 target and 100 non-target signals, namely, each set has 200 selection trials. In this experiment, all channels employed a 10-Hz lowpass filter, for we only needed to have the P3 components enhanced and the bandwidth of P3 components are limited as <5 Hz.

The classification rate of four single channels and their in-phase average combinations were tabulated in Table 1. In the table, CH1, CH2, CH3, and CH4 represented Fz, Cz, Pz, and Oz, respectively. The classification results from Fz were not ideal since the correct rate was only 70%. The low classification rate may be due to that P300 components were not stable in channel Fz (see Fig. 1 for detail), whereas the results in the other 3 channels reached a high classification rate of over 90%, reaching the highest rate of 94% in CH2 (Cz). Thereby, if simplifying the design of BCI is our first objective, relatively ideal results could be reached by only using the signals from a single channel such as Cz or Oz. The results also revealed the advantage of the experimental modality that we adopted.

Table 1 Classification rates in varied combinations and varied time sections (the classification rate Gy chance is 50%)/%

channel combinations	time section/ms					
	150–450	200–500	250–550	300–600	350–650	400–700
1 CH2+CH3	89.0	92.2	97.2	95.0	96.7	94.0
2 CH3+CH4	81.0	87.0	86.0	86.0	89.0	90.0
3 CH2+CH4	85.0	91.7	92.7	91.0	90.6	94.7
4 CH2+CH3+CH4	84.0	91.5	97.6	94.0	94.6	95.0
5 CH1	72.6	71.2	69.4	70.0	66.8	62.0
6 CH2	82.3	84.3	87.0	93.1	94.1	91.0
7 CH3	81.9	91.5	89.0	90.0	90.5	90.0
8 CH4	85.7	93.8	90.1	90.5	93.6	89.0

The in-phase averages of signals from varied channels were done in every selection trial. These averaged signals subsequently as features were classified by SVM algorithm. From Table 1, it is of little assistance in promoting classification rate by using a combination trick with CH4 (Oz). It is shown in Table 1 that the classification rate from a single CH4 is 93.8%, from CH2 is 94.1%, from combination 2 is 94.7%, and from combination 3 is 90%, respectively. Combination 1 (CH2+CH3) generates the best classification rate of up to 97%, which occurs in the time section 250–550 ms.

The reason why the classification rate of CH4 in combination with other channels is not as high as that turned out by combinations of CH2 (Cz) and CH3 (Pz), or even lower than the results from single channels, can be explained from Fig. 1. It is shown in Fig. 1 that the P3 components have satisfactory coherence in the three channels, which is helpful for promoting the classification rate. However, it should be noticed that in the time interval around 250 ms, the P2 components in Cz and Pz are in-phased which will help enhance features after time-lock averaged. On the contrary, the waves in Oz around 250 ms are negative, namely N2, whose superimposition with waves from other channels will weaken the features.

4 Conclusions

From the above discussion, we can see that utilizing the visual evoked potential evoked by imitating-natural-reading modality as the communication carries between the brain and the computer possesses the advantage of high classification rates in single trial estimations. Exploiting signals from a single channel such as Cz or Oz, the single trial estimation rate could be up to 94%. To gain better classification rate, the paper systematically investigated how to use the in-phase average in channels trick to have the signal features enhanced and consequently to boost the classification rates. Experimental results showed that the average classification rate of up to 97% could be reached by using SVM as classifier and the in-phase averaged signals from Cz and Pz at 250–550 ms as its features. The results also indicate a feasible approach to promote the overall performance of BCI.

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