ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

The Possibility of Single-trial Classification of Viewed Characters using EEG Waveforms

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Abstract. Electroencephalograms (EEGs) contain responses to visual stimulus, however, signal noise often prevents these from being easily obtained. To classify EEG waveforms, a signal processing procedure using the relationship between EEG and ERP, which is the summation of EEG waveforms, was developed. The processing technique involves the prediction of signals using Support Vector Regression. The procedure was developed and applied to a Kanji recognition task used to classify viewing characters, symbols or Kanji. The accuracy of classification between using EEG waveforms with ERP references and without ERP references was compared. The accuracy with references was significantly more than by chance and was higher than EEG waveforms without references.

1 Introduction

Electroencephalograms (EEGs) have been used to observe the human visual perception process, such as its response to visual stimulus, and has also been used to detect mental actions such as in a Brain Computer Interface (BCI) [1]. EEGs are noisy data because a single stimulus at the scalp is quite small (5–$10\mu V$). Therefore some additional information, such as references, are often required to extract information which is significant from single-trial EEGs [2]. A conventional technique for reducing noise on EEGs is the use of event-related potential (ERP) [3]. To extract an ERP waveform, EEG waveforms which record responses to stimulus must be averaged as much as is possible. As ERP can indicate some feature of events, they may be used as a reference to extract distinct information from single-trial EEGs. The relationship between EEG and ERP is simple, but it can be a key to understanding waveforms of single-trial EEGs. This means that every EEG waveform of a visual stimulus contains an ERP waveform with some artifacts, and an appropriate signal processing method is required to reduce these artifacts. If the appropriate ERPs are extracted from a small number of trials, a reference can be created during EEG measurement of the calibration process.

The aim of this paper is to examine the feasibility of classifying characters, such as symbols or Kanji viewed by subjects in single-channel single-trial EEGs using an estimation procedure with Support Vector Regression (SVR) [4]. As

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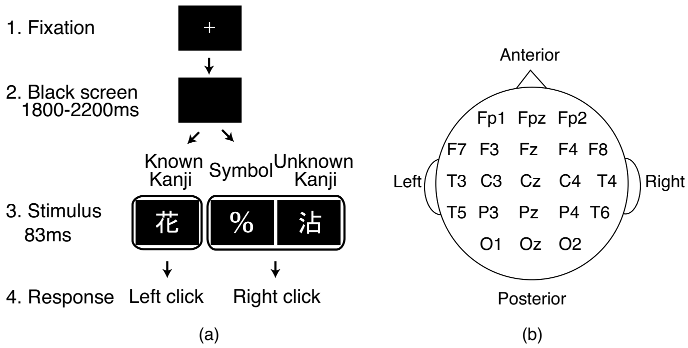

Fig. 1: Experimental task for Kanji recognition (a) and placement of electrodes (b).

a reference, SVR enhances the waveform features based on the relationship between EEG and ERP. The overall performance was evaluated for its accuracy in classifying characters in test samples viewed by subjects.

2 Method

2.1 EEG/ERP waveforms

2.1.1 Kanji recognition Task

An example of EEG and ERP waveforms was extracted from a Kanji recognition task [5, 6]. This experiment examined the Kanji recognition process in accordance with the differences in ERP waveforms among Kanji which were known, Kanji which were unknown, and symbols. The number of trials for each kind of stimuli was 100. A total of 200 trials were analyzed for each subject. The experimental task is depicted in Figure 1(a). The procedure was as follows: (1) The subject clicked the left button of a mouse to start the trial. (2) A black screen which gave a random delay of 1.8-2.2 *sec.* was then presented. (3) A image of a character (either a known Kanji, an unknown Kanji, or a symbol) was presented briefly (83 *msec.*). (4) The subject had to report if the image presented was a known Kanji or unknown Kanji by clicking the mouse's left or right button respectively. Four subjects who were 23-25 years old participated in this experiment.

The EEGs were recorded from 21 scalp electrodes which included Fpz, Oz, and 19 other electrodes, according to the international 10-20 system, and using an electrocap manufactured by Electro-cap International. Figure 1(b) shows the placement of electrodes. A ground electrode was placed on the forehead. All scalp electrodes were referenced to the subject's ear lobes. The signals were amplified and 0.5-100 Hz band pass filtered using a BIOTOP amplifier from NEC. The signals were stored in a PC that had a 512 Hz sampling rate. After being recorded, the signals were digitally filtered to reduce line noise below 40 Hz. Trials containing an EOG amplitude of more than 70 μV were removed from the subsequent analyses, because of the large artifactual influences of eye movements on the EEGs [7]. Each subject's single trial raw EEGs were recorded from every electrode from 100 $msec.$ before to 1000 $msec.$ after stimulus onset in all correct trials, and baseline voltages were subtracted from these raw EEGs. As a baseline for each trial and for each electrode, we used the average voltage in the preceding 100 $msec.$ interval before stimulus onset during the trial. Correct trials were trials in which the subject correctly discriminated between the characters or symbols presented. Extracted ERPs on the Fz electrode are summarized in Figure 2. There were significant differences between waveforms for symbols and known Kanji. In this paper, we focused on EEG waveforms for symbols and known Kanji on the Fz electrode because EEGs on the frontal area were activated during the discrimination task.

2.2 Classification of single-trial EEGs

EEG waveforms from the Fz electrode were classified into two groups using the Support Vector Machine (SVM) technique, depending on whether subjects viewed symbols or known Kanji. Here, Fz was chosen because the frontal area was activated to select a button. Therefore, only trials with correct responses were selected. Rates of correct selection averaged over 90% [5]. All EEG waveforms for each subject were standardized in advance, to permit some signal processing to be applied.

2.2.1 Classification without ERP references

The first 20 trials showing both symbols and Kanji were selected to create a training data set for each subject. A test data set was created using the rest of data. For the training data, classification labels for symbols or Kanji were given to each trial data set, which consisted of significant response periods (300 data points, 0∼586 msec.). The periods were extracted after repeated trials and errors. The classification was conducted using SVM with Gaussian kernel. Here, x_i is defined as EEG potentials, t is defined as the stimulus given, and the training data set comprises 300 input vectors $\mathbf{x} = (x_1, \ldots, x_{300})$, with corresponding target values: $t \in \{-1 : symbol, +1 : Kanji\}$. The standard deviation (STD) for the Gaussian kernel was controlled from 1 to 9.

After the training procedure, the classification model was applied to the test data set, and the accuracy of classification was evaluated. A practical calculation was conducted using the $SVMTorch$ package [8, 9].

2.2.2 Classification with ERP references

To extract the relationship between EEG and ERP, two ERPs for symbols and Kanji respectively were extracted from the training data set for each subject. To predict an appropriate signal in response to ERP waveforms, a regression

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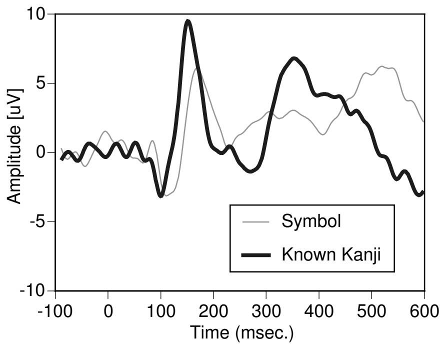

Fig. 2: ERP waveforms of symbol and Kanji character stimuli from the Fz electrode.

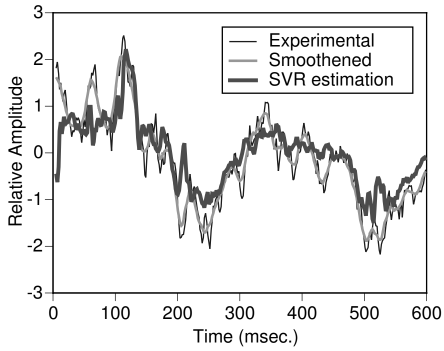

Fig. 3: An example of pre-processed EEG potentials.

function from single-trial EEG to ERP has been created using the SVR technique. Here, x_i is defined as EEG potentials, and y_i is defined as ERP. The estimated ERP $\hat{y_k}$ for the empirical potential y_k at the time position k is reproduced from time series data samples comprising 10 input vectors $\mathbf{x_k}$, as follows: $\mathbf{x_k}$=$(x_{k-9}, \ldots, x_k), \hat{y_k} = f(\mathbf{x_k})$. The parameters of SVR were set as a standard deviation for Gaussian kernel ($STD' = 2$) and a width of error pipe ($eps = 0.5$). This regression training procedure was conducted on a training data set which consisted of both EEGs of symbols and Kanji for each subject. Therefore, the regression prediction reflects both ERP features of symbols and Kanji.

The regression trained model was applied to all EEG data (training and test data sets), and the predicted EEG signals were created with consideration to the relationship between EEG and ERP. All EEG data were smoothened before training and prediction.

The final step, which is the classification of waveforms, is a common procedure. The classifications are: using EEG waveforms with ERP references and using EEG waveforms without using ERP references. The exception was that classification was conducted using SVR-predicted signals.

3 Results and Discussion

An example of the regression predicted using SVR is illustrated in Figure 3. This figure indicates three levels of pre-processing for a Kanji trial in a test data set. The fine line shows experimental observations at the Fz electrode, and the gray line shows smoothened data, and the bold line shows the predicted signal using the relationship between EEG and ERP. Although there is little difference between experimental and smoothened data, the predicted signals are partially different from the others, for example in between 200$\sim$250 $msec$.

The accuracy of classification between using EEG waveforms with ERP refer-

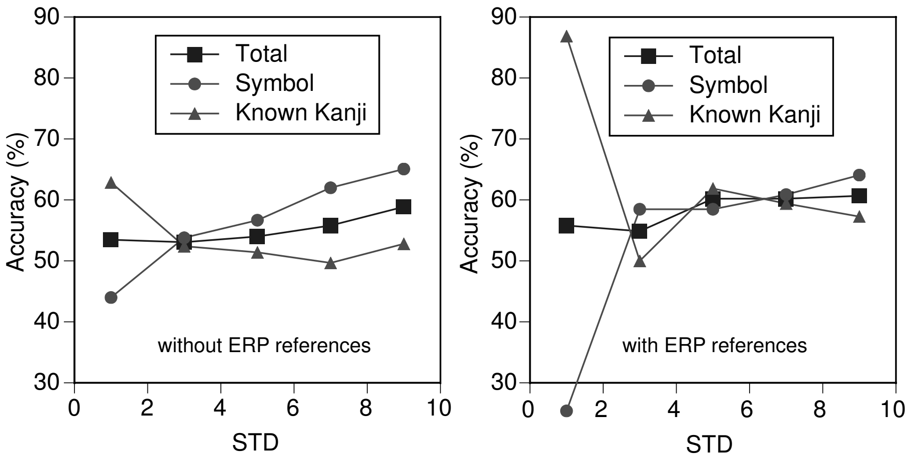

Fig. 4: Classification accuracy: with and without ERP references.

ences and without using ERP references is summarized in Figure 4. A parameter, the STD of the Gaussian kernel, was controlled from 1 to 9 while searching for the optimal accuracy of classification. The total number of symbols of the test data set was 284, and the total number of Kanji was 286.

According to the figure, the accuracy of the classification of symbols increases with STD, while the accuracy of the classification of Kanji decreases with STD. There is a trade-off relationship in both classifications, particularly when STD=1 using SVR preprocessing. The accuracy across all STD values with SVR-preprocessing is slightly higher than for STD values without preprocessing. In particular, the accuracies of symbols and Kanji are significantly above the chance level for STD when $STD = 5, 7, 9$ using a non-parametric test ($p < 0.05$) [10]. This means that characters viewed by subjects can be classified using pre-processed Fz single-trial EEGs. There is no condition where the accuracy of classification of both symbols and Kanji without ERP references is above the chance level. The accuracy of either symbols or Kanji stays at the chance level at some point across all conditions, however. These results provide evidence that ERP as a reference can make a significant contribution to signal processing for EEGs.

Although significant accuracy of classification was achieved, the level of accuracy remained low. To improve this performance, many other parameters should be considered. For example, the number of training data samples. According to the proposed procedure, a greater amount of training data may refine the reference, as the relationship between EEG and ERP will be clearer when the number of summations increases to reduce the effect of the noise of the EEG signals. If other parameters for classification and regression procedures were fine-tuned, classification accuracy may be improved. In addition, multi-channel data can also be used to improve classification accuracy. This improved performance should be tested in accordance with the increased number of channels and the increased number of observation areas on the scalp. These will be a subject of our further study.

4 Summary

We proposed a signal processing procedure for estimating the accuracy of classifying characters viewed by subjects in single-trial EEGs. The signal processing of waveforms was based on a prediction which took into the account the relationship between EEG and ERP, using support vector regression. As a result, the accuracy of classifications using ERP references was significant, and was higher than the accuracy of classification without references. This suggests that the procedure using the relationship between EEG and ERP is effective, and it is possible to conduct single-trial classifications of characters viewed subjects, using EEG waveforms.

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