Fast and Reliable P300-Based BCI with Facial Images

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Abstract

A P300-based brain-computer interface (BCI) often called "P300 speller" is a promising approach to help disabled people communicate with external world. However, the spellers using letters or symbols as stimuli usually require more than 5 repetitions to achieve high classification accuracy due to weak P300 evoked potential. We propose a suitable platform which has 8 command intuitive interface and uses human's facial images as flashes. The experimental results from on-line tests demonstrated that our P300-based BCI with facial images achieved over 90% accuracies by using only two repetitions. We also analyzed off-line EEG data using two or three channels and 2 paradigms achieved over 80% accuracies. In addition, we found that the latencies of event-related potentials evoked by a clockwise flash order were shorter than that evoked by a random flash order.

1 Introduction

An electroencephalographic (EEG) brain-computer interface (BCI) can provide a non-invasive, low cost, non-muscular means of direct communication between a human brain and a computer or a robot [1, 2]. One of the most reliable and promising multi-command BCI system is based on P300 evoked potential paradigm. Most of P300-based BCI platforms exploit so called P300 speller with small abstract elements like letters and symbols arranged in the form of a matrix where each row and column is intensified in a random sequence [1]. Recently, big progresses have been made in optimization of the P300 speller, for example, on color and intensity of stimulation [3], size of the matrix [4], EEG electrode locations [5] and classification algorithms [6]. Most of the spellers using letters or symbols as stimuli require more than 5 repetitions to reliably extract P300 evoked potential since the P300 evoked potential is relatively weak and occurs amid other ongoing EEG activities. Our objective in this paper is to demonstrate how to enhance or increase P300 evoked potentials by suitably designed stimuli.

We present a novel P300-based BCI whose commands are intensified by natural images of human faces – the affective face driven paradigm (AFDP). In this paper we use P300-based BCI that has 8 independent commands to navigate, for example, a robot arm or a wheel chair moving in 8 different directions. Our experiments demonstrated that P300-based BCI using AFDP showed higher accuracies than that a gray/white flash of abstract symbols.

2 Methods

We tested 6 paradigms illustrated in Figure 1. The central colored arrow image shows a target or an output as a feedback. The other arrow images indicate control commands and the part is intensified sequentially during each trial. We prepared two different flash orders: random (R)

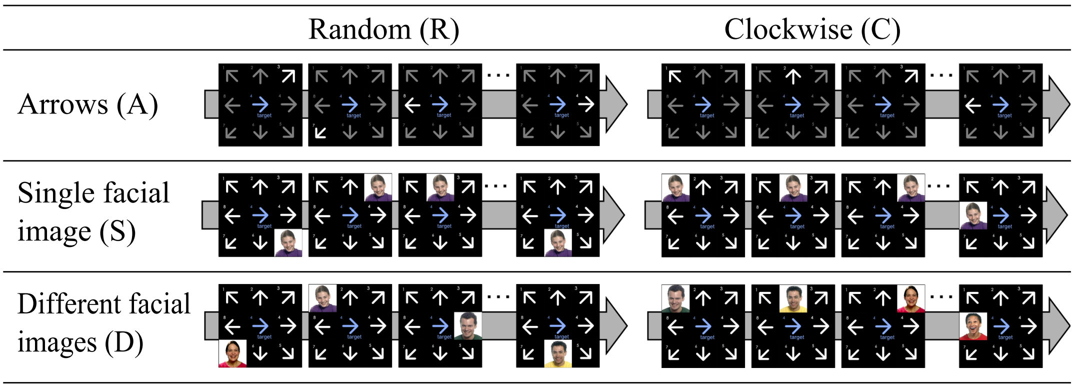


Figure 1: Illustration of visual stimuli for novel BCIs. The background black screen with 8 arrows was displayed continuously. The facial images or white arrows were flashed in random or clockwise order during 100 milliseconds (ms). The pause between two consecutive flashes was 20 ms. The top left panel shows a paradigm referred to as RA in which arrows are flashed randomly. In top right paradigm CA, arrows are also used as flashes but they flashed in clockwise order. RS paradigm means that a single face is displayed randomly. In CS paradigm the single face is flashed clockwise. In RD paradigm different facial images chosen randomly are used and finally in CD paradigm different facial images are flashed clockwise.

and clockwise (C) order. We also exploited three types of flash representations: arrows (A), a single facial image (S), and an image randomly selected from different facial images (D). The representation (A) is a gray/white symbol flicker but the other flash representations employ an natural image of human faces as stimuli. We randomized the experimental order to avoid order effects.

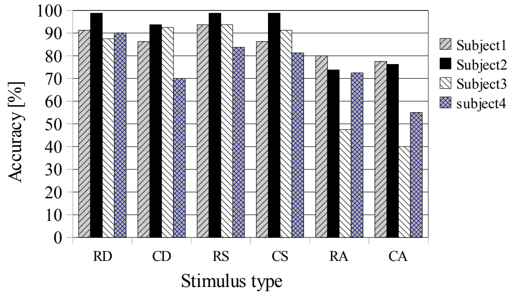
In our experiments, 4 healthy subjects were instructed to focus on a target arrow image cued by a center arrow image and silently count how many times the target was flashed. In a training stage, 16 targets were shown and each target was flashed 5 times. In a run of on-line test stages, 16 targets were shown but the number of target flashes to output a result was only 2 times. We repeated 5 runs for each stimuli. Subjects were seated in a comfortable chair placed 60 cm from a 17 inch LCD screen. Each stimulus cell size was 6×6 cm on the screen. We recorded EEG data and computed on-line classification accuracies. EEG signals were recorded at Fz, Cz, P3, Pz, P4, PO7, Oz and PO8 site following the 10-20 international system and each channel data was amplified by g.USBamp (Guger Technologies, Austria). The average of two mastoid electrodes was used as reference and the ground electrode was placed at AFz.

The 8 channel EEG data with 256 Hz sampling rate were filtered by a 50 Hz notch filter and a bandpass filter between 0.5 and 30 Hz and moving average was applied. Then the signals were down-sampled to 64 Hz. 700 ms buffers were made from each start time of a stimulus, subtracting baseline correlation by using 100 ms pre-stimulus data. After all arrows were intensified twice, each buffer was reconstructed into a feature matrix in which rows were feature vectors of all channels and columns indicated the stimuli. After that linear discriminant analysis (LDA) classifier was used to calculate the posterior probability of each column of the feature matrix, which was provided as Discriminant Analysis Toolbox by Dr. Michael Kiefte [http://www.mathworks.com/matlabcentral/fileexchange/189-discrim]. Finally, each probability was averaged to find the maximum score of all 8 arrows, taking it as an output.

3 Results

On-line classification performances of 6 paradigms are shown in Figure 2 (a). A classification accuracy was calculated as (# correct outputs) / (# total outputs). The number of flash repetitions

(a)



(b)

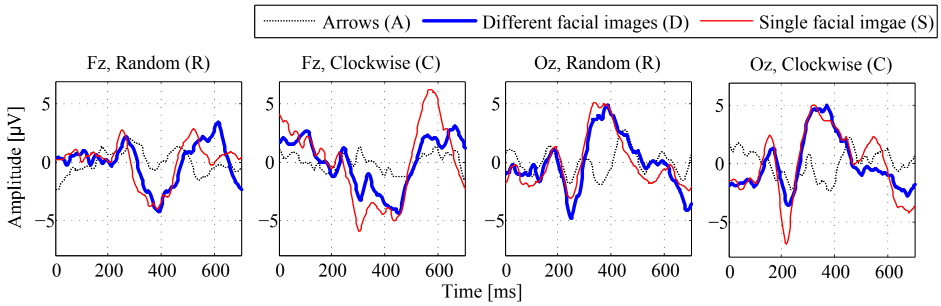


Figure 2: (a) On-line performance of our (8-channel) BCI system for four subjects. (b) Examples of averaged event-related potential waveforms obtained from training data of second subject.

for an output was only 2 times. Classification accuracies of RD, RS and CS, which were related to facial images, were over 80% for all subjects, while that of RA and CA were less than 80%. Every subjects achieved over 90% individually in one of paradigms related to facial images. Clockwise order stimulus CS which contained no randomness also worked with more than 80% accuracy.

Figure 2 (b) shows an example of averaged EEG waveforms of training sessions. Peak-to-peak voltages of the waveforms around 300 ms were over 5 μV when the arrows were intensified by different facial images or the single facial image, though the flashes by arrows evoked peaks below 5 μV. Also the latencies of event-related potentials evoked by the clockwise flash order were shorter than that evoked by the random flash order.

To be practical, the number of EEG electrodes should be minimum. We analyzed off-line EEG data using one, two and three channel combinations. Classifiers were built from the recorded training data. The number of repetitions was also 2 times.

Figure 3 depicts the off-line accuracies calculated by combinations of EEG channels for all 6 paradigms, where the four subject accuracies were averaged. Among one channel off-line classification results, Oz site accuracies of RD, CD, RS and CS paradigm showed over 50% though Fz, Cz and Pz site accuracies were less than 50%. Among two channel combinations, RD and RS paradigm accuracies of Cz&Oz and Pz&Oz showed above 80%. Also we tested three channel combinations. The RD, RS, and CS paradigm accuracies with Cz&Pz&Oz, P3&P4&Oz and PO7&Oz&PO8 also achieved above 80%. But RA and CA paradigm accuracies of those channel combinations were less than 60%.

4 Discussion

In the AFDP, features at Oz site enhanced its classification performance. Among the one channel off-line accuracies shown in Figure 3, only RD, CD, RS, CS at Oz site, in which facial images were used, showed over 50% classification accuracies. In Figure 2 (b), Oz site waveforms of the single and different facial images showed over 5 μV peak-to-peak voltages and this feature might have

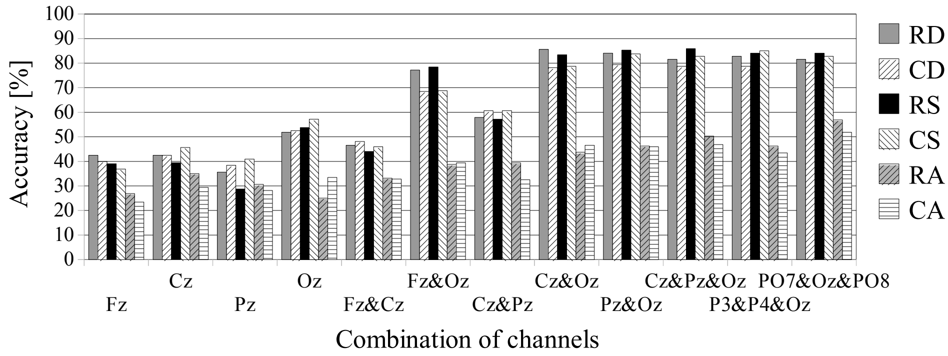


Figure 3: Off-line performance of our BCI systems using one, two and three channel combinations.

contributed to the classification accuracy. Taking those results into consideration, the features in Oz site were influenced by facial perception or were the mixture of visual evoked potentials from the occipital cortex. Thus the facial images increased the classification accuracies.

5 Conclusion

We have designed, implemented and preliminary tested new visual stimuli for P300-based BCI. Through the on-line experiment using only two repetitions, flashes with a single facial image and different facial images showed over 90% accuracies. According to averaged waveforms we found that the waveform of flashes related to faces evoked higher peak-to-peak voltage compared to flashes with arrows. Also in the off-line tests, even two or three channels data of EEG we have obtained over 80% accuracies. To our surprise, a paradigm which does not contain randomness also showed good performance. In our future work, we would like to extend these concepts to BCI system to control a robot arm, optimizing the stimulus, algorithms and functions.

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