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Input Interface Using Event-Related Potential P3

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Abstract— **This paper refers to a basic study toward the goal of developing a simple and easy-to-use input interface based on P3 components of visual, event-related potentials. Because contamination from eye movements and eye blinks is a problem, a method for removing eye movement artifacts from electroencephalogram (EEG) signals by applying an independent component analysis un-mixing matrix was proposed and implemented. Input character decisions were executed using a support vector machine (SVM) for judging the P3 existence of a single stimulus. The performances were compared while varying the number of channels of EEG signals, the types of feature vectors, and the ratio of the number of data used for training the SVM. The results indicated that three EEG signal channels (Fz, Cz, Pz) were enough to remove artifacts related to eye blinks and vertical eye movements and could be used to make a decision about input characters. The number of trials necessary to decide the input characters was ten on average. The best ratio achieved for the number of training data of targets and non-targets was 1:2. These results should be confirmed using a larger number of data sets.**

I. INTRODUCTION

The concept of moving an object just to make it think has often been discussed in science fiction. Recently, it has become a reality as a result of extensive research in the field of brain computer interfaces (BCIs). The BCI that uses scalp electroencephalograms (EEGs) is the most practical type because it can be realized via non-invasive measurement without large-scale equipment. There are two kinds of BCIs that use scalp EEGs: one uses spontaneous EEG and the other uses event-related potentials (ERPs). For the ERP-based BCI, many approaches use P3 (or P300) components. P3 is a late component with a latency of 250 to 800 ms and is considered to be related to the cognitive function of the brain. Its amplitude increases by focusing attention on the events (Fig. 1). P3 cannot be observed in a single EEG trace because of background activity. Therefore, P3 is acquired by averaging some tens of EEG segments clipped from the original trace triggered by the onset of the events.

P3Speller is a well-known BCI application that uses P3[1] and it is expected to eventually serve as a communication tool for patients with amyotrophic lateral sclerosis (ALS) [2]. For the P3Speller, a 6×6 matrix of characters is presented on a display, and one of the matrix rows or columns is successively and randomly intensified. The user's task is to focus attention on a certain character that is to be input and to count the number of times the character is intensified. One trial is composed of 12 intensifications (six rows and six columns), and is repeated a few dozen times. ERPs are obtained for each row and each column. The row and column that shows the largest P3 component are selected. The output is the character at the intersection of the selected row and the selected column (Fig. 2). Many studies have been conducted on the P3Speller. Y. Liu [3] reports a 98.2% precision rate when only four trials with six EEG channels are used.

In the present study, we developed an input interface based on the P3Speller that can be applied not only to ALS patients but also to healthy people, with a view to operating a robot or controlling an environmental system as well as inputting characters. In such situations, eye movements and eye blinks often occur, particularly the latter. Therefore, a real-time technique to remove ocular-related artifacts is essential. In addition, to make it easy to use, the number of EEG channels and the number of trials to be used must be minimized.

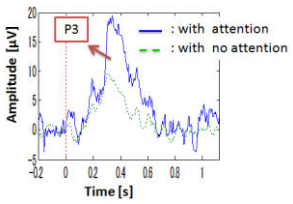

Fig. 1. An example of P3 components (unpublished data)

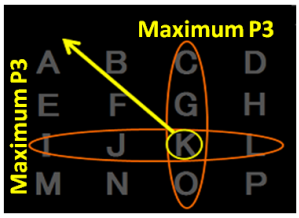

Fig. 2. Display that is similar to P3Speller

II. ARTIFACT REMOVAL USING INDEPENDENT COMPONENT ANALYSIS

Initially, we tried to remove the artifacts caused by ocular movement and eye blinks by using independent component analysis (ICA)[4]. The data we collected consisted of two sections: the first was obtained during an eye movement session and the second section was obtained during a character input session. In the eye movement session, the participants were asked to perform horizontal and vertical eye movements and eye blinks as instructed. The eye movement session was introduced because a sufficient number of horizontal and vertical eye movements and eye blinks are necessary to obtain their related independent components (ICs) from the EEGs in ICA.

A paradigm similar to that of the P3Speller was used for the character input session. A 4×4 matrix of characters was presented to each participant. The participants were asked to refrain from suppressing their eye movements and eye blinks, but then actively allow them in the second session in order to obtain the EEGs contaminated with ocular artifacts. EEG data measured during the two sessions were concatenated, and this was decomposed by ICA. The ICs that showed high coefficients of correlation with Electro-oculogram (EOG)

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during the first section were removed as ocular artifact components. An example is shown in Figs. 3–5. Fig. 3 shows EOG and EEG data for the three parts of the eye movement section: the horizontal eye movements, the vertical movements, and the eye blinks. Fig. 4 shows the coefficients of correlation between EOG and each IC. The artifact components can be identified by selecting the component showing a high coefficient of correlation with EOG automatically. Fig. 5 shows EEG data after the ocular artifact data were removed. These procedures were tested for various EEG data sets composed of different numbers of channels from different regions. As a result, it was possible to remove the automatic detection and ocular artifact components by using the EEG data from four to six channels, including the lateral frontal regions and the central region.

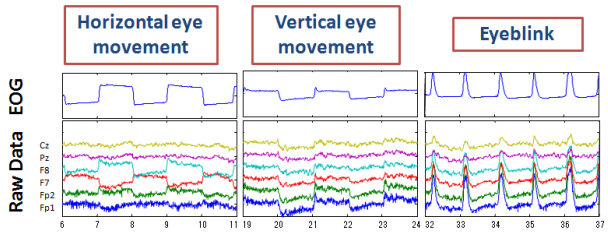

Fig. 3. EOG and EEG raw signals during an eye movement session

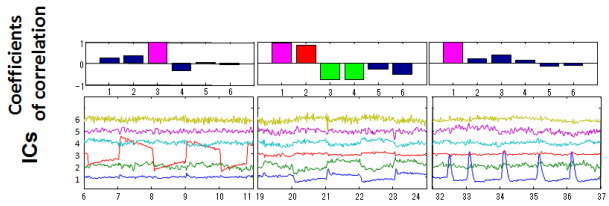

Fig. 4. Selection of artifact components depending on the coefficients of correlation between ICs and EOG

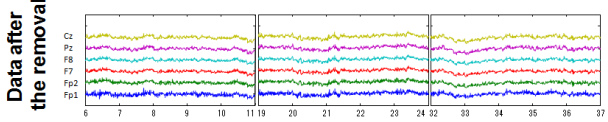

Fig. 5. EEG signals after artifact removal

III. SAVING THE CONVERGENCE TIME OF ICA BY APPLYING THE UN-MIXING MATRIX

As for the method shown in Section II, the convergence time for ICA becomes a problem in judging the input character in one moment. Therefore, we proposed a method for the detection and removal of ocular artifact components [5]. This does not use ICA for the data to be judged but instead applies an un-mixing matrix for acquiring ICs that were obtained previously using another data set. This method is based on the hypothesis that the un-mixing matrix for one healthy person provided by ICA does not change too much if the electrode placement is the same.

The detailed procedure is shown below. First, EEG data are collected during the eye movement session described in Section II, and an additional session is implemented in which the participants are required to execute an oddball task. In the oddball task, the participants are given target stimuli (such as a reversed letter “C”) and non-target stimuli (such as a normal letter “C”) in a ratio of 2:8 and are asked to count target stimuli. The oddball session was added because the eye movement-related ICs were not obtained separately if the un-mixing matrix obtained from EEG data of an eye movement session alone was applied to that of the input character session. Second, ICA is given to the connected data of two sessions and an un-mixing matrix and its inverse matrix are obtained. The ICs related to ocular movement are identified using the coefficients of correlation with EOGs during the eye movement session. The corresponding rows and columns are removed from the un-mixing matrix and its inverse matrix, respectively. The product of these matrices is applied to the EEG data of the input character trials. Fig. 6 shows the procedure of the proposed method.

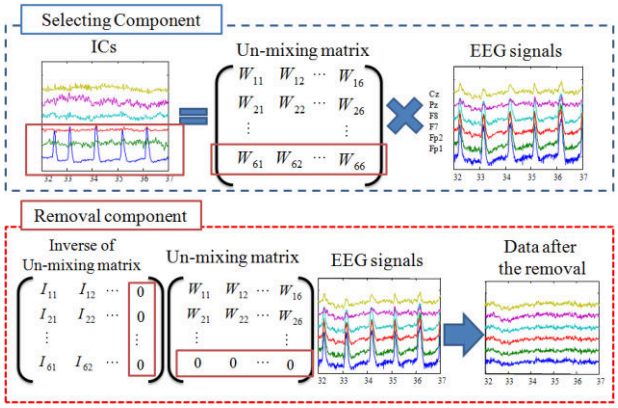

Fig. 6. Procedure of the proposed method

Five healthy undergraduate students (A-E) participated in the experiment after giving a written informed consent. The sequence of an eye movement session, an oddball task, and an input character session was termed a data set. For each participant, six to seven data sets were collected.

In most data sets, one of the ICs was identified as a horizontal eye movement-related component, and another was identified as the component related not only to the vertical eye movements but also to the eye blinks. One more component related to vertical eye movements was found in some data sets. The rows of the un-mixing matrices corresponding to each identified component for each participant are superimposed in Fig. 7, which shows that they are highly reproducible.

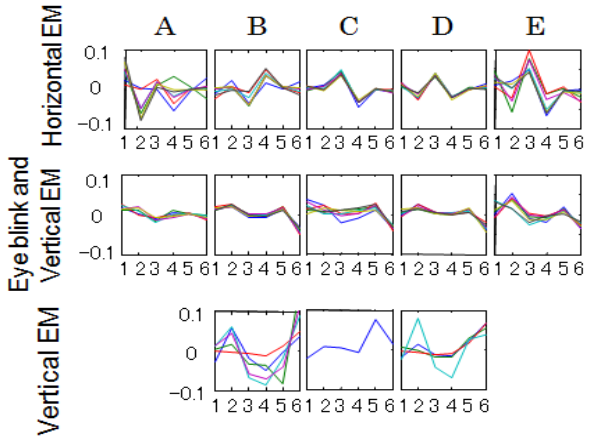

Fig. 7. Weights of the un-mixing matrivsx for each component

The effect of the artifact removal using the proposed method was tested by comparing the EEG data before and after the removal. Fig. 8 shows an example of this. The EEG waveforms before the removal were similar to EOG; however, after the removal, the similarity disappeared. These observations suggest that the ocular artifacts were removed successfully.

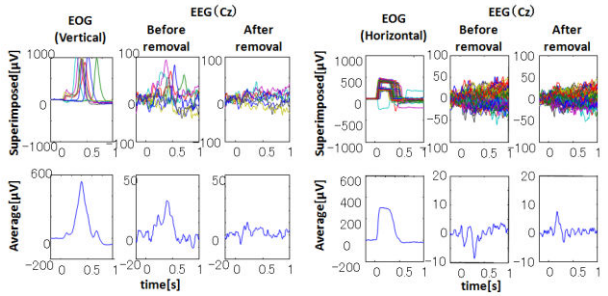

Fig. 8. Before and after removal of ocular components (left: before and after removing the vertical components. right: before and after removing the horizontal components)

IV. JUDGMENT OF INPUT CHARACTER USING A SUPPORT VECTOR MACHINE

Next, we worked on a method to judge an input character using a small number of electrodes and trials. The P3 components are usually obtained by averaging EEG data for approximately 20 trials. The support vector machine (SVM) was introduced so that the existence of P3 is determined using single-trial data. Methods that uses the SVM have previously been reported in many papers (for example, see [6]). So we tried to reduce the number of trials and the number of EEG channels. We also examined the effects of this method for creating feature vectors and preparing training data sets on the discrimination performance. As for the feature vector, the averaged waveform of each channel to reduce noise is compared with the connected one. In addition, for the SVM training sets, the ratio of the target trials (including the input character where the EEG is expected to include P3 components (TG)) to non-target trials (not including the input character (NTG)) was changed from 1:1 to 1:3.

A. *Data acquisition*

The participants were three healthy male undergraduate students who gave a written informed consent. EEG signals from 19 locations in the 10/20 system and the horizontal and vertical EOGs were measured with a digital multi-channel amplifier for biological signals (Polymate AP1132, TEAC). The acquired EEG signals were sampled at 200 Hz after being amplified with 10 μV/mm sensitivity and a 3.0 s time constant.

Initially, the data from the eye movement session for calculating the un-mixing matrix were collected. The participants were asked to perform horizontal/vertical eye movements and eye blinks according to the instructions on the screen. They were also required to do an oddball task. One hundred stimuli composed of reverse letter "C"s and normal letter "C"s in a ratio of 2:8 were presented at a stimulus interval of 500 ms. The participants were instructed to count the number of times that reverse "C"s appeared.

After the oddball session, a character input session was executed. A 5×6 character matrix based on P3Speller was presented to the participants using an original program written in MATLAB language. One of the rows and columns of the matrix was successively and randomly highlighted by changing the foreground color from yellow to green at 600 ms intervals. The participant's task was to focus on a character that was input under the instruction of the experimenter, and he then had to count the number of times that the character was highlighted. Each trial comprised 11 stimuli, which means every row and every column was highlighted once in a trial. Thirty trials were executed for an input character. The sequence of an eye movement session, an oddball task, and three input character sessions was called a data set. Three to five data sets were collected for each participant.

B. *Application and assessment of the proposal method*

We analyzed the EEG signals, which were derived from seven scalp locations (Fp1, Fp2, F7, F8, Fz, Cz, Pz), by using the linked earlobe as a reference. Fp1, Fp2, and Fz were selected as the locations with the largest eye blink-related artifacts. F7 and F8 were selected to obtain the horizontal eye movement component. Fz, Cz, and Pz were chosen as the locations where P3 components could be clearly detected.

We then sought to compare an easier-to-use method—judging the performance using only three channels, Fz, Cz, and Pz—with the seven-channel system used above, based on the assumption that eye movements can be suppressed in some situations.

The components of eye blinks/vertical eye movements were removed from the EEG signals obtained during the character input session by using the method previously described. In addition, the components of horizontal eye movements were removed only when seven channels were used. After artifact removal, the EEG signals were low pass-filtered with a high cut frequency of 7 Hz to reduce alpha activities.

The baseline correction was performed using the averaged value of the signal for 0.1 s duration just before the trigger point by setting a trigger point at the onset of each stimulus. The filtered and baseline-corrected EEG signals from selected channels were extracted from 0.1 s to 0.6 s after every trigger point and used as the feature vector for SVM, being averaged over the channels or being connected in a sequence (Fig. 9).

The SVM was trained to discriminate the stimuli that caused P3 (TG) from those that did not cause P3 (NTG) using one of the previously described types of feature vectors by varying the ratio of TG and NTG numbers used for training from 1:1 to 1:3.

The basic method for deciding the input character was as follows. The number of stimuli judged to be TG by SVM in the trials was counted for each row and column, respectively. The row that showed the largest number was selected, as was one column. The character at the intersection of the selected row and the selected column was chosen as the target character.

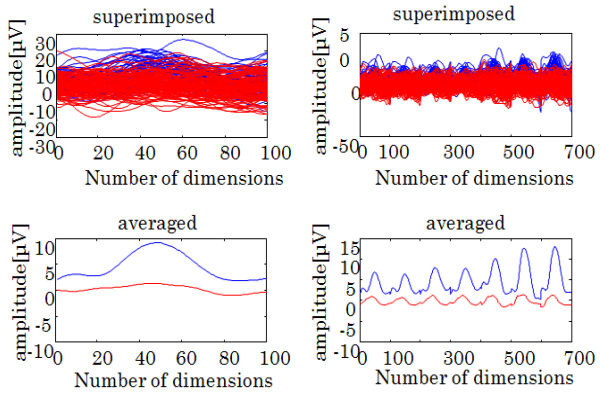

Fig. 9. Two types of feature vectors made by averaging EEG signals over channels (left) and by connecting them in a sequence (right) (upper panel: superimposed EEG signals, lower panel: averaged signals, blue: target, red: non-target)

The performance was evaluated by determining the number of trials needed to obtain the correct answers. The rows and columns were selected as above, increasing the number of trials (N) to be considered one by one. The maximum number of trials was 30. Then, 30 pairs of selections were obtained for an input character. The number of trials necessary to obtain the answer (that is, to decide the input character) was found as the minimum number of i where the pair selected in i-th selection was the same as that of all j-th selections, where $j > i$.

C. *Results*

P3 components were observed clearly only for the first characters of each data set for two participants, which may have been caused by fatigue or attention deficit. Therefore, six input characters (three per participant) were analyzed. One of the three characters (11 stimuli × 30 trials) was used for the training data, and the other two characters were used for evaluation. Therefore, six combinations per participant were obtained and used as the evaluation sets.

Fig. 10 shows the results in the average and minimum/maximum of i for each method for two participants ("A" and "B"). The correct answer was obtained on average in approximately 10 trials. When the training ratio was 1:2 (center panel of Fig. 10), the averages and the difference between the maximum and the minimum tended to be smaller. Fig. 11 shows the relationships between the number of used trials and the number of correct answers when the training ratio was 1:2. The best performance (six trials) was found in participant "A" when only three channels and the connected feature vectors were used. The averaged feature vectors could not yield good results; this suggests that the noise reduction effect achieved by averaging the signals over the channels was not provided because the number of channels was small. A ratio of 1:2 was considered to be advantageous because our algorithm for deciding the input characters is more tolerant of false negatives than false positives.

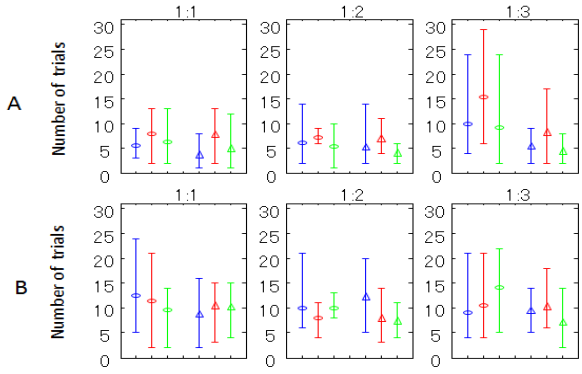

Fig. 10. Average (○,△) and minimum/maximum trials needed to obtain correct answers for two participants (upper: A, lower: B), three ratios (left: 1:1, center: 1:2, right: 1:3), three combinations of used channels (blue: artifact removal; 7ch, SVM; 7ch, red: artifact removal; 7ch, SVM; 3ch, green: artifact removal; 3ch, SVM; 7ch), and two feature vectors (○: averaged, △:connected)

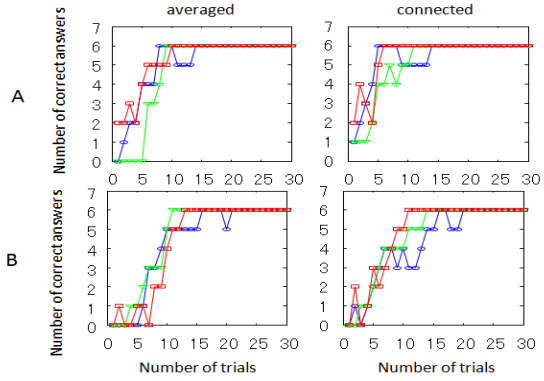

Fig. 11. Comparison of the number of trials needed to obtain correct answers in the case of a ratio of 1:2 for two feature vectors (left: averaged, right: connected, the colors indicate the same combinations as those in Fig. 10)

ACKNOWLEDGMENT

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