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Single trial method for Brain-Computer Interface

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Abstract— **Electroencephalogram (EEG) related to fast eye movement (saccade), has been the subject of application oriented research by our group toward developing a brain-computer interface(BCI). Our goal is to develop novel BCI based on eye movements system employing EEG signals online. Most of the analysis of the saccade-related EEG data has been performed using ensemble averaging approaches. However, ensemble averaging is not suitable for BCI.**

In order to process raw EEG data in real time, we performed saccade-related EEG experiments and processed data by using the non-conventional Fast ICA with Reference signal(FICAR). The FICAR algorithm can extract desired independent components(IC) which have strong correlation against a reference signal.

Visually guided saccade tasks and auditorily guided saccade tasks were performed and the EEG signal generated in the saccade was recorded. The EEG processing was performed in three stages: PCA preprocessing and noise reduction, extraction of the desired IC using Wiener filter with reference signal, and post-processing using higher order statistics Fast ICA based on maximization of kurtosis.

Form the experimental results and analysis we found that using FICAR it is possible to extract form raw EEG data the saccade-related ICs and to predict saccade in advance by about 10[ms] before real movements of eyes occurs. For single trail EEG data we have successfully extracted the desire ICs with recognition rate about 70%.

In next steps, saccade-related EEG signals and saccade-related ICs in visually and Auditorily guided saccade task are compared in the point of the latency between starting time of a saccade and time when a saccade-related EEG signal or an IC has maximum value and in the point of the peak scale where a saccade-related EEG signal or an IC has maximum value. As results, peak time when saccade-related ICs have maximum amplitude is earlier than peak time when saccade-related EEG signals have maximum amplitude. This is very important advantage for developing our BCI. However, S/N ratio in being processed by FICAR is not improved comparing S/N ratio in being processed by ensemble averaging.

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I. INTRODUCTION

Brain-computer interfaces (BCIs) have been the subject of research efforts for several decades [1][2]. The capabilities of BCIs allow them to be used in situations unsuitable for the conventional interfaces. BCIs are used to connect a user and a computer via an electroencephalogram (EEG). The EEG is related to emotion, motion, and thought. Therefore, there is the potential that BCI is a technology allowing normal and mobility-impaired persons to control a computer in such a way that movement on the part of the user is not required. Moreover, the *Quality of Life* for severely handicapped users is expected to be improved by using BCIs to connect these users to computers.

EEG related to fast eye movement (saccade) have been studied by our group toward developing a BCI eye-tracking system that operates by using saccade-related EEG [3]. In previous research, EEG data was analyzed using the ensemble averaging method. Ensemble averaging is not suitable for analyzing raw EEG data because the method needs many repetitive trials.

Recording EEG data repetitively is a critical problem to develop BCIs. Overcoming this critical problem is essential to realize practical use of BCIs for single trial EEG data.

In studies of the conventional interfaces, researchers used time-frequency analysis, such as short-time Fourier transform and wavelet transforms, to process raw EEG data. Generally speaking, however, α wave, β wave, etc., are observed widely over the human head and a frequency wave can be related to many functions of the brain. Therefore, it is vital to extract from raw EEG data components which are related to various mental tasks.

Recently, the independent component analysis (ICA) method has been introduced in the field of bio-signal processing as a promising technique for separating independent sources [4],[5],[6],[7]. The ICA method can process raw EEG data and find features related to the various activity of one individual. Therefore, ICA overcomes the problems associated with ensemble averaging, and it observes the waveforms of the EEG data.

There have been research results reported for applying ICA to EEG signals and magnetoencephalogram (MEG) signals. T-P Jung et al. applied ICA to removing electrooculogram (EOG) noise from EEG data [5]. S. Ikeda et al. applied ICA to removing signal noise introduced by environmental noises [6]. A. C. Tang et al. applied ICA to the task of estimating dipoles using MEG data [7]. In the field of EEG and MEG researches, the main application for ICA is to noise reduction and dipole estimation. Hence, there

has been little research undertaken to extract the desired EEG signals related to motion and emotion in applications of the ICA method.

There are many algorithms that are used in the field of ICA [8][9][10]. However, it is unfortunate that in trying to develop BCIs, researchers have found that most of these algorithms cannot be used to extract one desired signal. In the research reported here, the Modified "Fast ICA with Reference signal (FICAR)"[11] method was applied to the analysis of saccade-related EEG data. The FICAR method can extract a desired signal by using a reference signal.

In this paper, visually guided saccade tasks and auditorily guided saccade tasks are performed in a magnetically shielded dark room and the EEG signals generated during a saccade are recorded. Saccade-related EEG signals are analyzed by using the FICAR method. The results are compared with those obtained using ensemble averaging and the FICAR. The extraction rate obtained for the saccade-related components and the time at which the saccade-related components were extracted are described.

II. FAST ICA WITH REFERENCE SIGNAL (FICAR)

The ICA method is based on the following principle. Assuming that the original (or source) signals have been linearly mixed, and that these mixed signals are available, ICA recognizes in a blind manner a linear combination of the mixed signals, and recovers the original source signals, possibly re-scaled and randomly arranged in the outputs.

The $\mathbf{s} = [s_1, s_2, \cdots, s_n]^{\mathbf{T}}$ means n independent signals from mutual EEG sources in the brain, for example. The mixed signals $\mathbf{x}$ are thus given by $\mathbf{x} = \mathbf{A}\mathbf{s}$, where $\mathbf{A}$ is an $n \times n$ invertible matrix. $\mathbf{A}$ is the matrix for mixing independent signals. In the ICA method, only $\mathbf{x}$ is observed. The value for $\mathbf{s}$ is calculated by $\mathbf{s} = \mathbf{W}\mathbf{x}$ ($\mathbf{W} = \mathbf{A}^{-1}$). However, it is impossible to calculate $\mathbf{A}^{-1}$ algebraically because information for $\mathbf{A}$ and $\mathbf{s}$ are not already known. Therefore, in the ICA algorithm, $\mathbf{W}$ is estimated non-algebraically. The assumption of the ICA algorithm is that $\mathbf{s}$ is mutually independent. In order to calculate $\mathbf{W}$, different cost functions are used in the literature, usually involving a non-linearity that shapes the probability density function of the source signals. However high-order statistics, such as the kurtosis, are widely used as well. The kurtosis shows how independent the signal is because the kurtosis is the classical measure of nongaussianity [9],[12]. The Fast ICA [12] which is one of the ICA algorithms, is based on a cost function minimization or maximization that is a function of the kurtosis ($\kappa(\mathbf{w}^{\mathbf{T}}\mathbf{x}) = E\{(\mathbf{w}^{\mathbf{T}}\mathbf{x})^{\mathbf{4}}\} - 3[E\{\mathbf{w}^{\mathbf{T}}\mathbf{x}\}^{\mathbf{2}}]^{\mathbf{2}} = E\{(\mathbf{w}^{\mathbf{T}}\mathbf{x})^{\mathbf{4}}\} - \mathbf{3} \parallel \mathbf{w} \parallel^{\mathbf{4}}$; $\mathbf{w}$ is one of the rows of $\mathbf{W}$) [9]. Then the Fast ICA changes the weight $\mathbf{w}$ to extract an independent component with the fixed-point algorithm.

From among the several ICA algorithms, we selected the Modified "Fast ICA with Reference signal (FICAR)"[11] algorithm to use in this study. This algorithm can extract only the desired component by initializing the algorithm with a priori information on the signal of interest. In other words, it can extract the independent component closest to the reference signal in the mean-squared error (MSE) sense.

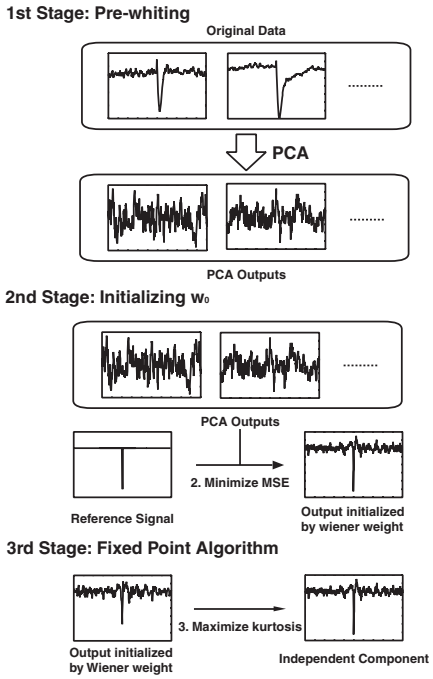

Fig. 1. Conceptual three stage for extraction desired ICs.

Figure 1 shows an overview of the procedures of the proposed algorithm. First, the principal component analysis (PCA) outputs are calculated from original recorded signals to speed up the convergence of the algorithm. Second, this algorithm initializes $\mathbf{w}_k$ ($k = 0$; k is the iteration number.). The purpose of this algorithm is to find from the mixed vector $\mathbf{x}$ one given component s_i of the source signal $\mathbf{s}$. This is done by using some priori information included in a signal, d, correlated with s_i, i.e., $E[ds_i] \neq 0$. The algorithm does this by using all the components of the input vector $\mathbf{x}$ in a linear combination. Thus, we have $u = \mathbf{w}^{\mathbf{T}}\mathbf{x}$, d is a reference signal and the error is given by $\varepsilon = d - u$. The weights are updated by the minimization of MSE given by $E[\varepsilon^2]$. To calculate the MSE, we used the least mean square (LMS) which is one of the algorithms for calculating the MSE. After some calculations, the optimum weight (also called the Wiener weight) to minimize the MSE was found to be $\mathbf{w}_* = E[d\mathbf{x}]$. In this algorithm, $\mathbf{w}_0$ is initialized by $E[d\mathbf{x}]$ (see [11] if you need details of $\mathbf{w}_0$). Third, this algorithm calculates $\mathbf{w}_{k+1}$ by $\mathbf{w}_{k+1} = E[\mathbf{x}(\mathbf{w}_k^{\mathbf{T}}\mathbf{x})^3] - 2\mathbf{w}$ to maximize kurtosis. and then this algorithm can extract a independent component closest to a reference signal or strictly speaking independent component which is correlated with the reference signal.

III. EXPERIMENTAL SETTINGS

There are four tasks in this study (See Fig.2). The first task is to record the EEG signals during a saccade to a visual target that is to the right or left side of the subject. The second task is to record the EEG signals as a control condition when

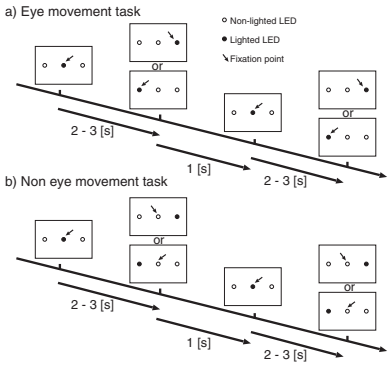

Fig. 2. Experimental tasks.

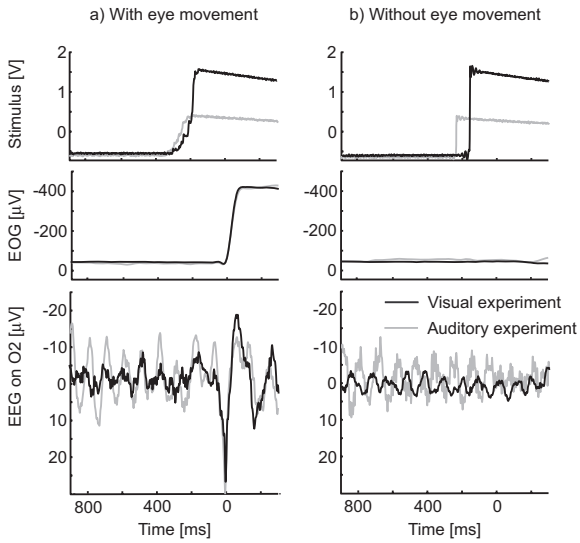

Fig. 3. Saccade-related EEG recorded on O2.

a subject dose not perform a saccade even though a stimulus has been displayed. First task and second task are called visual experiments. On the other hand, The third task is to record the EEG signals during a saccade to a auditory target that is to the right or left side of the subject. The fourth task is to record the EEG signals as a control condition against the third task when a subject dose not perform a saccade even if a stimulus has been turned on. The third task and fourth task are called auditory experiments. Each experiment is comprised of 50 trials in total: 25 on the right side and 25 on the left side.

The EEG signals are recorded through 19 electrodes (Ag-AgCl), which are placed on the subject's head in accord with the international 10-20 electrode position system. The Electrooculogram (EOG) signals are simultaneously recorded through two pairs of electrodes (Ag-AgCl) attached to the top-bottom side and right-left side of the right eye.

All data are sampled at 1000[Hz], and stored on a hard disk for off-line data processing after post-amplification. The raw data is filtered by a high-pass filter (cut-off 0.52 [Hz]) and a low-pass filter (cut-off 120 hz). The EOG data is recorded through a high-pass filter (cut-off 0.1 [Hz]) and a low-pass filter (cut-off 15 [Hz]).

In this paper, the shape of the reference signal is that of an impulse signal having one peak. This shape is caused for two reasons. First, the saccade-related EEG has a sharp change like am impulse. Second, the main components of an EEG signal are the neural responses, and the waveform of the neural responses is resembled to impulse.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Results of ensemble averaging

Fig.3 shows the experimental results obtained for "Subject A" when the visual stimulus on the right side is illuminated. This EEG data is processed with ensemble averaging and high-pass filter (cut-off 4 [Hz]). The data is averaged 20 times because some of the trial data include artifact related to eye blinking and other body movements. Next the high-pass filter is applied to reduce the EOG background low-frequency noise. Fig.3-a and 3-b show the data with and without eye movement to right side, respectively. Black lines indicate results in visual experiments and gray lines represent results in auditory experiments. The top boxes show the voltage generated in response to the LED becoming illuminated. The middle boxes indicate the potential of EOG signals. The increase of EOG signals means an eye movement to right side. The bottom boxes represent EEG potential recorded at the right occipital lobe (at O2 in the international 10-20 electrode position system). The horizontal axes indicate the time span, where 0 [ms] indicates the start point of the eye movement. In the case of no eye movement, 0 [ms] is defined as the calculated point in time following the trigger, which is delayed by the mean latency of the EOG start after the stimulus onset. The vertical axes indicate the measured potential. The amplitude of the EEG signal is sharply changed just before eye movement in Fig. 3-a. However, there was no change for the case of no eye movement. The same tendency was observed for all five subjects in the case of both visual and auditory experiments. In this study, we re-confirm the saccade-related EEG has a sharp change just before saccade. It is reported in a previous study that this type of sharp change of the EEG signal is related to saccadic eye movement [3].

In order to focus on features of saccade-related EEG signal, a time when saccade-related EEG signals have maximum amplitude and maximum amplitude is checked in Table I. Amplitude was defined as $n = \frac{\bar{x}-\mu}{s}$; where $\bar{x}$ is mean of EEG potential during 1000 [ms] before saccade, μ is maximum amplitude, and s is standard deviation during 1000 [ms] before saccade.

Peak time when saccade-related EEG signal is from -6 [ms] to -2[ms] (Ave. = -3.5, STD = 1.1) and n is from 4.4 to 9.3 (Ave. = 7.1, STD = 1.1) in Table I. From Table I, peak time of saccade-related EEG signals was observed before saccade.

TABLE I

PEAK TIME AND AMPLITUDE ON SHARP CHANGE OF EEG.

	In visual experiments		In auditory experiments	
	Peak time [ms]	$n = \frac{\overline{x}-\mu}{s}$	Peak time [ms]	$n = \frac{\overline{x}-\mu}{s}$
	Right/Left	Right/Left	Right/Leftt	Right/Left
A	-3 / -2	8.6 / 9.3	-4 / -4	6.3 / 7.0
B	-5 / -3	6.3 / 7.8	-6 / -2	4.4 / 4.7
C	-3 / -4	7.0 / 6.9	-4 / -4	6.3 / 7.0
D	-3 / -2	8.2 / 8.2	-3 / -3	8.0 / 6.7
E	-3 / -3	7.8 / 7.9	-4 / -5	6.5 / 7.3
Ave.	-3.4 / -2.8	7.6 / 8.0	-4.2 / -3.6	6.3 / 6.5
STD	0.9 / 0.8	0.9 / 0.9	1.1 / 1.1	1.3 / 1.1

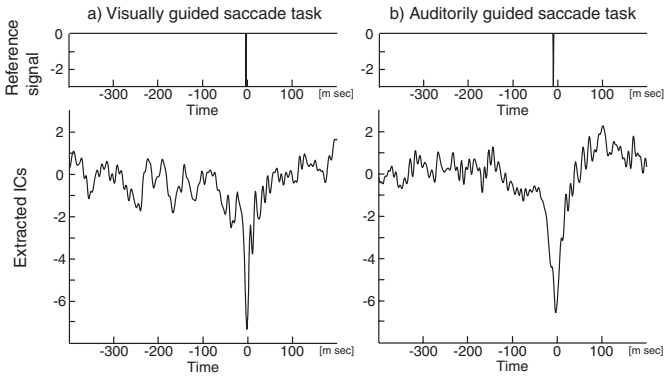

Fig. 4. Extracted signals for FICAR in visual and auditory experiments.

B. Results of FICAR

We prepared about 500 reference signals for use in this experiment. As describe above, a reference signal has one peak point because waveform of a reference signal is a impulse wave. The signals differ in the time it took each to peak. The first reference signal has a peak when the stimulus is illuminated, and the time when the second reference signal has a peak is (*the time when the first reference signal has a peak*) + 1 [ms]. The time when each reference signal has a peak is (*the time when the previous reference signal has a peak*) + 1 [ms]. The final reference signal peaked in 300 [ms] after an eye movement.

Fig.4 shows the experimental results obtained when a subject move his eyes toward a visual or auditory target on the right side. These data are processed using the FICAR against the raw EEG data. The results shown is for Subject A, Trial #1. The left figures indecate results in visual experiments and the right figures show results in auditory experiments. Top boxes represent the shapes of reference signals and bottom boxes indecate the amplitude of the ICs obrained by using the FICAR. The horisontal axes in these graphs represent the time course, where 0 [ms] indecates the start point of eye movement.

The results show that the amplitude of the signal obtained by the FICAR is sharply changed when a reference signal is set just before eye movements. The shape of the IC that is obtained when the peak of the reference signal occurred prior to an eye movements resembles the shape obtained with the ensemble averaging method (See Fig.3 and 4). The IC which has a peak just before eye mvements bears a resemblance to the features of ensemble averaging in respect to the time when the potential incurs a sharp change. In the case of all subject and trials, this component is extracted. Therefore, we conclude that this pre-movement component is related to the saccade-related IC.

C. Extraction rate

Next, we will determine how many the saccade-related ICs are obtained by using the FICAR. Table II-(a) and II-(b) represets the rate for extracting saccade-related ICs from the raw EEG data. The extraction rate is defined by ratio:

(*the number of trials in which saccade-related IC are extracted*)
/ (The total number of trials).

TABLE II

EXTRACTION RATE FOR EXTRACTING SACCADE-RELATED ICS IN VISUAL AND AUDITORY EXPERIMENTS.

(a) In visual experiments

Subject	Subject B	Subject C	Subject D	Subject E
Right / Left	Right / Left	Right / Left	Right / Left	Right / Left
60%/88%	60%/64%	52%/64%	80%/80%	88%/80%

(b) In auditory experiments

Subject A	Subject B	Subject C	Subject D	Subject E
Right / Left	Right / Left	Right / Left	Right / Left	Right / Left
92%/84%	68%/72%	76%/68%	60%/80%	52%/88%

The lowest rate was 52%. However, the rate for most of the subjects was over 60% and the highest rate was 92%. The average rate was 72.8%.

It is difficult to explain the reason why there are low rate 52%. The feature of EEG signal is not always generated or observed in real world the number of fired neuron is not always the same in all trial. Therefore, in single trial processing, the feature were not always extracted successfully.

In the ensemble averaging results, a sharp change of the EEG signal is recorded each time; however, a subject had to perform the task over 20 trials. On the other hand, in the case of the FICAR, the rate for extracting saccade-related IC is below 100%. However, the saccade-related IC was extract in only two trials, and the ICA method extracted the same feature as the ensemble averaging results in a shorter time than ensemble averaging. Therefore, from the results, we find that the ICA method is more suitable for extracting saccade-related components than the ensemble averaging method. In other words, we have confirmed that ICA is potentially useful for developing BCI.

D. Comparison between saccade-related EEG signal and IC

In order to compare the saccade-related EEG with saccade-related IC, we focus on a time when saccade-related ICs have a maximum amplitude and maximum amplitude. Table III shows a time when saccade-related ICs have maximum amplitude and maximum amplitede in results of FICAR. Definition of n was the same as results of ensemble averaging. Value of each cell was calculated by averaging.

TABLE III

PEAK TIME AND AMPLITUDE ON SHARP CHANGE OF ICS.

	In visual experiments		In auditory experiments	
	Peak time [ms]	$n = \frac{\overline{x}-\mu}{s}$	Peak time [ms]	$n = \frac{\overline{x}-\mu}{s}$
	Right/Left	Right/Left	Right/Leftt	Right/Left
A	-12.7 / -12.7	5.6 / 5.2	-13.0 / -16.0	4.8 / 4.6
B	-8.9 / -11.9	3.3 / 5.6	-19.1 / -13.1	3.7 / 3.8
C	-7.8 / -12.5	3.5 / 4.8	–13.4 / -18.6	3.7 / 3.6
D	-12.4 / -16.1	5.9 / 6.1	-7.8 / -13.8	4.5 / 5.0
E	-13.8 / -15.1	6.8 / 6.4	-7.8 / -9.7	4.5 / 5.7
Ave.	-11.5 / -13.7	5.0 / 5.6	-12.2 / -14.2	4.3 / 4.5
STD	3.0 / 1.8	1.5 / 0.6	4.7 / 3.3	0.5 / 0.9

Peak time when saccade-related ICs have maximum amplitude is from -19.1 [ms] to -7.8[ms] (Ave = -12.9, STD = 3.3) and n is from 3.3 to 6.8 (Ave. = 4.9, STD = 1.0) in Table III. From Table III, features of saccade-related ICs were observed before saccade and these features were observed remarkably.

Comparing results of saccade-related EEG signal with results of saccade-related ICs, Peak time when saccade-related ICs have maximum amplitude is earlier than peak time when saccade-related EEG signals have maximum amplitude. This is big advantage in the case of developing proposed BCI, the alarm of inattentive driving, and the high-speed targeting system. However amplitude calculated as n in the case of saccade-related ICs is not larger than in the case of saccade-related EEG signal. Therefore, in the point of S/N ratio, results of ensemble averaging are better than results of FICAR. However, if pre-processing is used before EEG signals are processed by ICA, S/N ratio become better in the case of ICA results.

V. CONCLUSION

This paper present extraction of saccade-related ICs and compared features of saccade-related EEG signals and saccade-related ICs in the point of a time when saccade-related ICs have a maximum amplitude and maximum amplitude in visual experiments and auditory experiments. Our study shows that EEG signals related to saccade can be extracted by the ICA method. The extraction rate for the saccade-relate IC was 72.8%. This rate is not high enough to apply the ICA method to signal processing for BCIs. Therefore, EEG signals must be used with pre-processing. Comparing results of saccade-related EEG signals with results of saccade-related ICs, peak time when saccade-related ICs have maximum amplitude is earlier than peak time when saccade-related EEG signals have maximum amplitude. This is very important advantage for developing our BCI. However, S/N ratio in being processed by FICAR is not improved comparing S/N ratio in being processed by ensemble averaging.In the future, we will try to obtain a higher extraction rate for extracting the saccade-related ICs and to improve S/N ratio in being processed by FICAR using by advanced ICA algorithms and pre-processing.

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