RESEARCH OF SACCADE-RELATED EEG: COMPARISON OF ENSEMBLE AVERAGING METHOD AND INDEPENDENT COMPONENT ANALYSIS

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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 on-line. 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-realted EEG experiments and processed data by using the non-conventional Fast ICA with Reference signal (FICAR). Using the FICAR algorithm, we was able to extract successfully a desired independent components(IC) which are correlated with a reference signal. Visually 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 4[ms] before real movements of eyes occurs. For single trail EEG data we have successfully extracted the desire ICs with recognition rate 72%.

1. 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 BCIs can be used to connect normal and mobility-impaired persons to computers 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 various one's activity. 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, a visually guided saccade task is 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.

2. 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 destiny 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 (IC) 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 IC closest to the reference signal in the mean-squared error (MSE) sense.

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

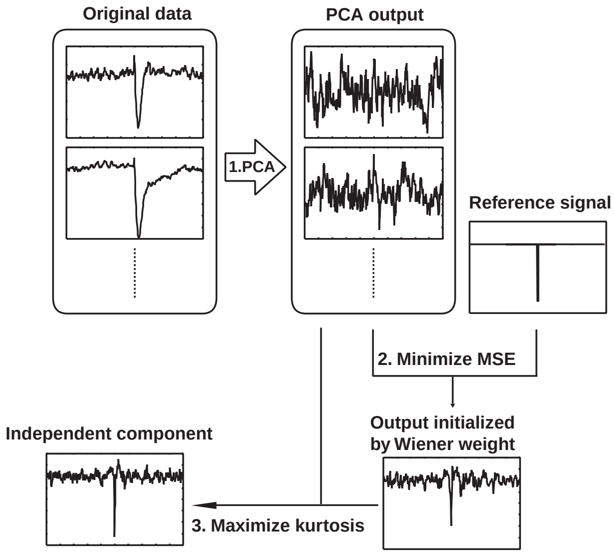

Fig. 1. Conceptual three stage for extraction desired ICs.

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 IC closest to a reference signal or strictly speaking IC which is correlated with the reference signal. If several reference signals are available then we can extract ICs correlated strongly with these reference signals one by one. The main advantage of our approach is fast extraction of desired ICs especially when the number of observation is large say 64 or more.

3. EXPERIMENTAL SETTINGS

There were two tasks in this study (see Figure 2). The first task was to record the EEG during a saccade to a visual target (LED) when a subject moves his eyes toward a visual stimulus that is on his right or left side. The second task was to record the EEG as a control condition when a subject does not perform a saccade even though a stimulus has been displayed. Each experiment was comprised of 50 trials in total: 25 on the right side and 25 on the left side of the head.

The experiments were performed in an electromagnetically shielded dark room to reduce the effect of electromagnetic noise and any visual stimuli in the environment. The visual targets were three LEDs placed in a line before the subject (see Figure 3). One was located 30-cm away from the nasion of the subject. The other two other LEDs were placed to the right and left of the center LED, each separated by 25 degrees from the center LED. They were illuminated randomly to prevent the subjects from trying to guess which direction the next stimulus would be coming from next.

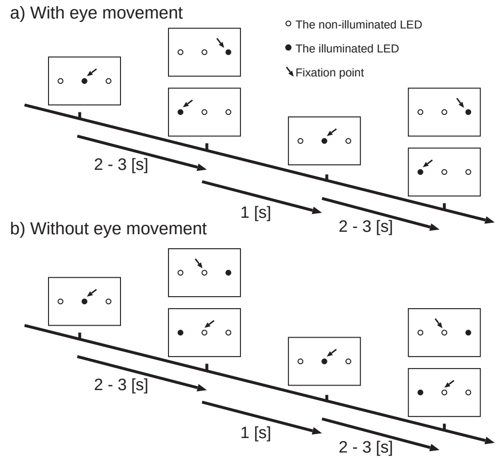

Fig. 2. Experimental tasks.

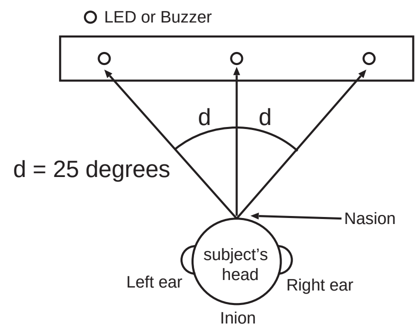

Fig. 3. Placement of LEDs.

The subjects were five 25-26 year-old male subjects all having normal vision.

The EEG was recorded through 19 electrodes (Ag-AgCl), which were placed on the subjects' head in accord with the international 10-20 electrode position classification system (see Figure 4). The EOG was 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 were sampled at 1000 Hz, and stored on a hard disk for off-line data processing after post-amplification. The raw EEG data was filtered by a high-pass filter (cut-off 0.53 Hz) and a low-pass filter (cut-off 120 Hz). The EOG data was 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 was used for two reasons. First, the saccade-related EEG has a sharp change like an impulse [3]. Second, the main components of

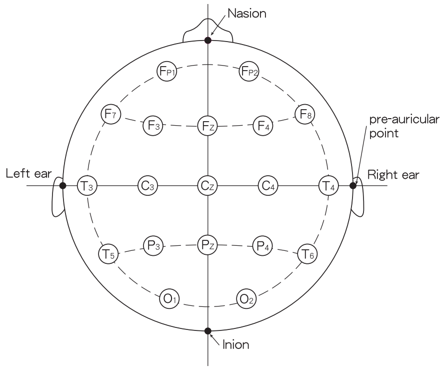

Fig. 4. International 10-20 electrode position classification system.

an EEG signal are the neural responses, and the waveform of the neural responses is resemble to impulse.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Results of ensemble averaging [3]

Figure 5 shows the experimental results obtained for "Subject A" when the visual stimulus on the right side was illuminated. This EEG data was processed with ensemble averaging and a high-pass filter (cut-off 4 Hz). The data was averaged 20 times because some of the trial data included artifact related to eye blinking and other body movements. Next, the high-pass filter was applied to reduce the EOG background low-frequency noise. Figures 5(a) and 5(b) show the data with and without right-eye movement, respectively. The top boxes represent the voltage generated in response to the LED becoming illuminated. The middle boxes show the potential of the EOG. The increase of the EOG means an eye movement to the right. The bottom boxes indicate the EEG potential recorded at the right occipital lobe (P_4 in the international 10-20 electrode position classification system). The horizontal axes indicate the time span, where 0 [ms] indicates the starting 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 was sharply changed just before eye movement in the case of an eye movement. However, there was no change for the case of no eye movement. The same tendency was observed for all five subjects.

In this study, we re-confirmed the saccade-related EEG has a sharp change just before saccade. It was reported in a previous study that this type of sharp change of the EEG signal is related to saccadic eye movement [3].

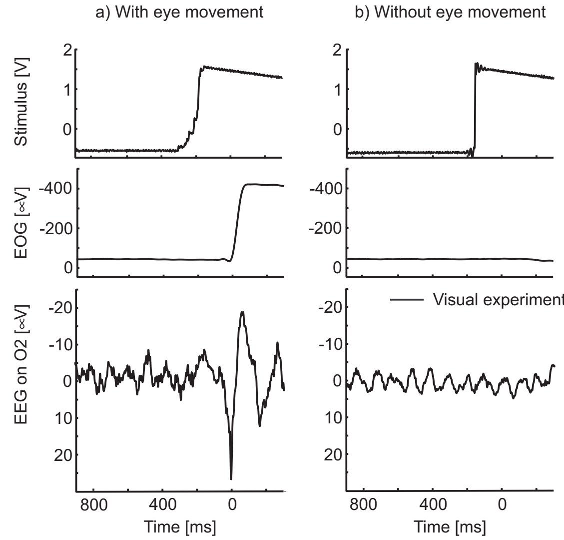

Fig. 5. EEG with and without eye movement to illuminated sources. (Recorded position is P_4.)

4.2. 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 differed in the time it took each to peak. The first reference signal had a peak when the visual target was illuminated, and the time when the second reference signal had a peak is *(the time when the first reference signal has a peak)* $+1[\mathbf{ms}]$. The time when each reference signal has a peak is *(the time when the previous reference signal has a peak)* $+1[\mathbf{ms}]$. The final reference signal peaked in 300 [ms] after an eye movement.

Figure 6 shows the experimental results obtained when a subject moved his eyes toward a visual stimulus on the right side. These data were processed using the FICAR against the raw EEG data. The result shown is for Subject A, Trial #1. Each graph shows the results obtained using a different reference signal. Reading from the top to the bottom, these graphs show the potential of the EOG, the shapes of the reference signals, and the value of the ICs obtained by using the FICAR. An increase of the EOG means an eye movement to the right side. "No data" in the graphs of the ICs obtained by the FICAR means that the algorithm of the FICAR was not convergent, and no IC was obtained for the FICAR. The horizontal axes in these graphs represent the time course, where 0 [ms] indicates the start point of eye movement.

The results indicate that the amplitude of the signal obtained by the FICAR was sharply changed when a reference signal was set in about -300 [ms] and just before eye move-

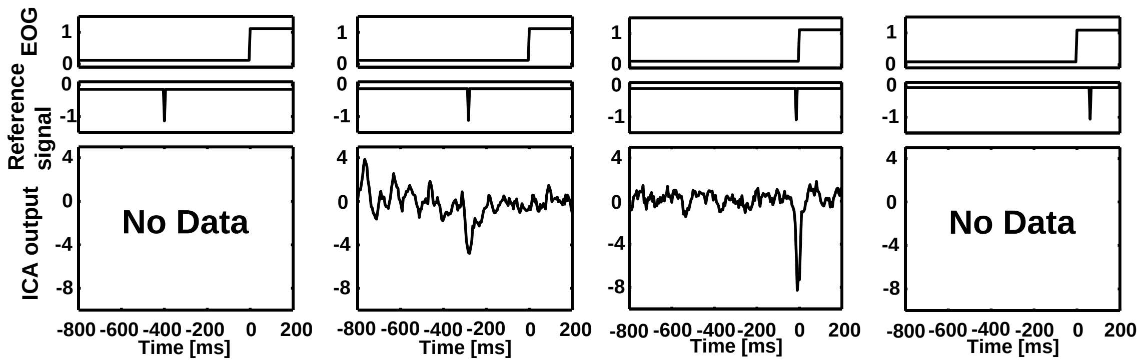

Fig. 6. Outputs of FICAR. (Subject A, Trial #1.)

ment. The shape of the IC that was obtained when the peak of the reference signal occurred prior to an eye movement resembles the shape obtained with the ensemble averaging method (Figure 5).

This result is not indicative of all the results we obtained. The IC which had a peak in -300 [ms] was not always successfully extracted. When we checked all results, we determined that we could not detect the rule to extract the IC which had a peak in about -300 [ms]. On the other hand, the IC which had a peak just before a saccade was extracted many times.

It is difficult to identify what is the IC which has a peak in -300 [ms] because features like that of the IC which has a peak in -300 [ms] were not recorded in the ensemble averaging and the IC which had a peak in -300 [ms] was not extracted for all subjects and all trials by the FICAR.

As we described above, a IC which has a peak just before eye movement 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 subjects, this component was extracted. Therefore, we conclude that this pre-movement component is related to the saccade-related EEG.

4.3. Extraction rate

Next, we will determine how many of the saccade-related ICs obtained by using the FICAR. Figure 7 represents 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)*.

The lowest rate was 48%. However, the rate for most of the subjects was over 60% and the highest rate was 88%. The average rate was 72%.

It is difficult to explain the reason why there are low rate 48%. The feature of EEG signal is not always generated in real world because 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.

Subject A		*Subject B*		*Subject C*		*Subject D*		*Subject E*	
Right	*Left*	*Right*	*Left*	*Right*	*Left*	*Right*	*Left*	*Right*	*Left*
64%	64%	72%	68%	48%	80%	80%	88%	84%	84%

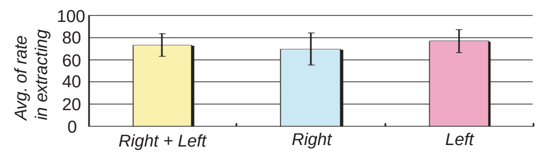

Fig. 7. Extraction rate for extracting saccade-related ICs.

In the ensemble averaging results, a sharp change of the EEG signal was 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 was below 100%. However, the saccade-related IC was extracted in only two trials, and the ICA method extracted the same feature as the ensemble averaging results in a shorter time than the ensemble averaging. Therefore, from the results, we found 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.

4.4. Time occurrence of saccade-related ICs

Figure 8 shows the times occurrence when the saccade-related ICs were extracted. The horizontal axis indicates the peak time of reference signals that can extract the saccade-related ICs. The vertical axis indicates the number of reference signals over a specified time that can extract the saccade-related ICs.

From about -20 [ms] the saccade-related ICs are extracted; the peak was at -4 [ms] in this graph.

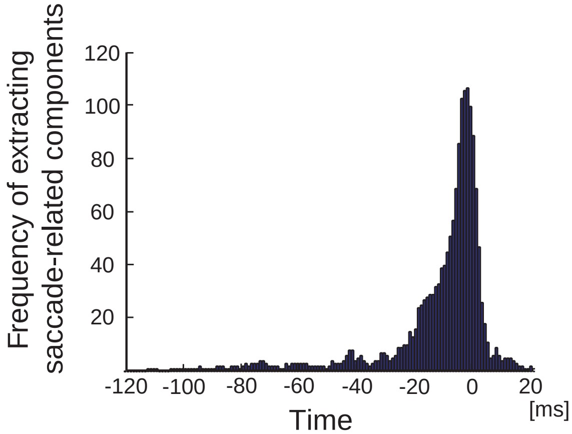

Fig. 8. Time when saccade-related ICs were extracted.

The saccade-related ICs were extracted just before an eye movement. Therefore, the starting point of the saccadic eye movement may be estimated by using the FICAR method. Hence, it is possible to develop an interface using this knowledge.

The global minimum point of saccade-related EEG potential processed by ensemble averaging is from -5 [ms] to -2 [ms] ($Avg. - 3.1[ms]$) [3]. This graph indicates that the peak time of the reference signals occurred at the time the saccade-related EEG had the global minimum point. Therefore, the saccade-related ICs are strongly related to the saccade-related EEG.

5. CONCLUSION

This paper presents method for extraction of saccade-related ICs obtained in visually guided saccade tasks. Saccade-related ICs were extracted by applying the FICAR method to raw EEG data: Our study shows that EEG signals related to saccade can be estimated by the ICA method. The extraction rate for the saccade-related ICs was 72%. This rate is high enough to apply the ICA method to signal processing for BCIs. The time when a saccade-related IC is extracted is just before an eye movement. Hence, the FICAR can predict when a saccade is generated.

In the future, we will apply the FICAR method to raw data obtained in the case of impaired eye movement and analyze the saccade-related independent components in more detail. Also, we will try to obtain a higher extraction rate for extracting the saccade-related ICs by using more advanced algorithms.

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