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研究論文

Preprocessing of Electroencephalograms by Independent Component Analysis for Spatiotemporal Localization of Brain Activity

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Abstract

The authors measured electroencephalograms (EEGs) from subjects when recalling several types of images. Each image presented consisted of four types of line drawings of body parts. During these experiments, the electrodes were fixed on the scalp of the subjects. However, recorded EEGs had multiple components, including muscle and brain potentials. Recently, independent component analysis (ICA) has been used for EEG analysis. ICA is a technical method for solving the so-called "cocktail party problem". We applied ICA to single-trial EEGs for preprocessing to obtain actual brain activity, and then attempted to estimate spatiotemporal brain activity using equivalent current dipole source localization (ECDL). Our results were almost identical with previous results using ECDL analysis on Event Related Potentials (ERPs). In this paper, we present experiments suggesting that ICA is effective as a preprocessing method for estimation of spatiotemporal brain activity using the ECDL and three-dipole model.

Keywords-Independent Component Analysis; Electro-encephalogram; Equivalent Current Dipole Localization Method; Brain Activity.

I. Introduction

According to research on the human brain, the primary processing of a visual stimulus occurs in V1 and V2 in the occipital lobe. Initially, a stimulus presented to the right visual field is processed in the left hemisphere and a stimulus presented to the left visual field is processed in the right hemisphere. Next, processing moves on to the parietal associative areas [1].

Higher order processing in the brain is associated with laterality. For example, Wernicke's area and the Broca's area are located in the left hemisphere in 99% of right-handed people and 70% of left-handed people [2, 3]. Language is also processed in the angular gyrus (AnG), the fusiform gyrus (FuG), the inferior frontal gyrus (IFG) and the prefrontal area (PFA) [4].

Using equivalent current dipole localization (ECDL) techniques [5] applied to summed and averaged electroencephalograms (EEGs), we previously reported that ECDs can be localized to the right middle temporal gyrus, and estimated in areas related to working memory for spatial perception, such as the right inferior or the right middle frontal gyrus for input stimulus of arrow symbols. Further, using Chinese characters as stimulus, ECD were also

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localized to the prefrontal area and the precentral gyrus [6-10].

To improve the signal-to-noise (S/N) ratio, generally single-trial EEG data are summed and averaged. This results in event related potentials (ERPs). When using such a method, the experiment should be repeated many times to gain accurate data. However, many repetitions can cause subject fatigue.

Recently, independent component analysis (ICA) [11] has been used to analyze acoustic and EEG data. ICA is a mathematical concept used to solve a problem, for example where a number of people are talking simultaneously in a room, and a listener is trying to follow a discussion (cocktail party problem). The human brain can solve this auditory source separation problem, but it is a complex problem for digital signal processing.

Moreover, EEGs used in brain research contain external sources of electric magnetic fields and/or muscle potentials from eye blinks of the subject for example.

In this paper, we used ICA to process single-trial EEGs, and attempted to remove artifacts from the subject's head movements. If effective, then the number of EEG measurement trials could be reduced significantly, that would reduce fatigue of the subject. Furthermore, as we have been using EEGs in a brain-computer interface (BCI) experiment in our laboratory, the use of ICA processing may increase discrimination accuracy.

To confirm the efficiency of ICA, we used an ECDL method for single-trial EEGs after application of ICA [11]. We compared these results with our previous results using ECDL on ERPs [12].

In section II, the ICA methodology is detailed. In section III, preprocessing of EEGs using ICA is described. In section IV, results of one dipole analysis using the ECDL method after ICA are shown. In section V, results of three- dipole analysis using the ECDL method after ICA are shown. In Section VI the results are discussed.

II. Independent Component Analysis

First, we consider unknown n signals generated from independent signal sources

$$s_1(t),\ s_2(t),\ \cdots,\ s_n(t), \tag{1}$$

and n measured signals that are linearly mixed with the original sources

$$x_1(t),\ x_2(t),\ \cdots,\ x_n(t). \tag{2}$$

Supposing that a linear relationship with a matrix A, which is independent of time, is

$$x(t)=As(t). \tag{3}$$

It is assumed that the original sources are connected linearly to the signals by a matrix A, as in (3). The purpose of ICA is to separate the signals into n independent components without knowledge of the matrix A, under the assumption of independence of $s(t)$. If a real matrix W exists, then by the following equation

$$y(t)=Wx(t), \tag{4}$$

the original signal can be recovered by reconstructing mutually independent $y(t)$. If $WA=I$ holds then, $y(t)$ coincides with $s(t)$, where I is a unit matrix. However, the equation $WA=PD$ is acceptable, because the order of the signals does not affect the isolation of the components of $y(t)$, where P is a matrix with one single row to each column and D is a diagonal matrix. Under one of the definitions of independence of signals, we determine W so that cost is minimized for one of the cost functions defined elsewhere.

This is the so-called "the cocktail party problem", a mathematical treatment of the effect of discerning the voice of interest from background noise.

III. Preprocessing of EEGs by ICA

In this study, we used the ICA analysis tool ICALAB (RIKEN Brain Science Institute, Japan) for single-trial EEG preprocessing (Figure 1), which is implemented in MATLAB (MathWorks, Natick, MA, USA). The algorithm we used was Fixed-Point ICA, where correspondence of the input and output is held. For EEG data from 19ch, based on the international 10–20 system, ICALAB is able to obtain the independent components and reconstructs the measured EEG data. In this study, we extracted 19ch component data on ICALAB, an then obtained 19ch EEG data ($y1$, $y2$, $\cdots$, $y19$) on the basis of the independent components.

Furthermore, as the Fixed-Point ICA generates results for $y1$-$y19$ corresponding to the original 19ch EEG data, we applied the ECDL method to results from ICA to obtained ECDs, and then compared these using a three-dipole model and one-dipole model.

IV. One-Dipole Model of ECDL After Preprocessing with ICA

With regard to the EEG data in the present paper, we compared estimated results of the present study with that of our previous results using the ECDL method [12]. Figure 2 shows an example of ERPs obtained from our previous research. The estimated results from multiple brain areas according to latency are shown in Table I. An example of single-trial EEG data is shown in Figure 3, while an example of a single-trial EEG signal processed by ICA is shown in Figure 4.

After preprocessing by ICA, we analyzed the data using the one-dipole ECDL method, and compared the results with Table 1. According to ECD, coincident activity was observed in V1, the posterior central gyrus (PstCG) and the parahippocampus. However, the ICA results revealed no coincident activity estimated in language areas; i.e., Broca's area and Wernicke's area, and the fusiform gyrus, which is involved in cognition. In addition, the goodness of fit (GOF), an evaluation criterion of the estimated results used in the ECDL method, did not reach 99%.

In a preanalysis using the one-dipole ECDL method, we found partial concurrence with our previous results [8]. Figure 4 shows an example of estimated ECDs using the one-dipole ECDL method. Two cases are shown, one with disparsed ECDs and the other with concentrated ECDs.

To improve estimation accuracy, we applied ICA to a partial data, one half (from 1 to 1000 ms) and one forth (from 1 to 500 ms, and from 501 to 1000 ms). By narrowing the range of latency, the estimated brain parts were increased, but the GOFs were not improved.

V. Application of a Three-Dipole Model of ECDL After Preprocessing Using ICA

Next, we attempted to estimate spatiotemporal brain activity using a three-dipole model, which is more accurate than a one-dipole method, to reconstruct data from $y1$-$y19$ using ICA. In addition, considering the recording of ERPs in Figure 2, we modified the analysis range of latency from 2000 to 1000 ms. Figure 3 shows an example of the results applied to $y1$,

TABLE I Relationship between Estimated ECD and Latency in Event Related Potentials from Multiple Brain Areas

Estimated Part	V1	ITG	R ParaHip
Latency [ms]	131	323	393
R AnG	Wernicke	R Broca	R ParaHip
427	455	485	506
R PstCG	L FuG	R ParaHip	Broca
524	556	590	681

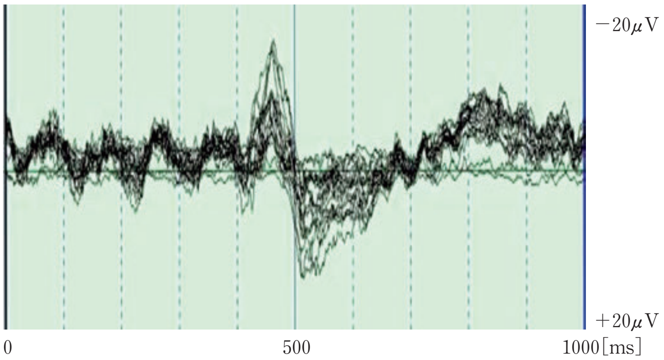

Figure 1　Event Related Potential

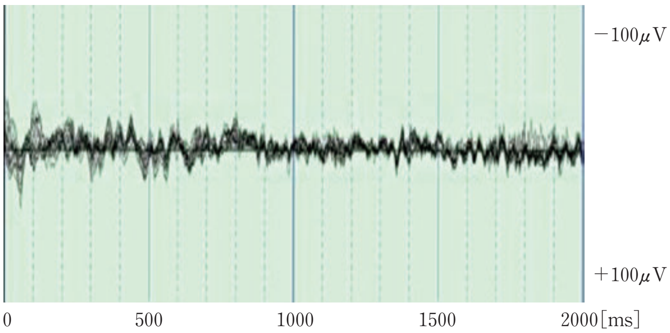

Figure 2　Example of single trial EEG data

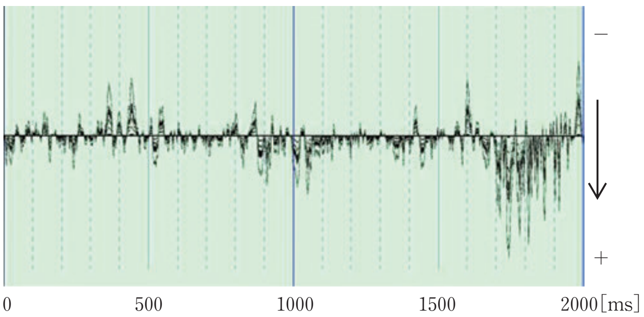

Figure 3　Example of single-trial EEG data processed by ICA (Component $y1$)

among reconstructed data using ICA from $y1$-$y19$. In Figure 3, the sign and ratio is significant in the y axis. In addition, Table II shows estimated results of brain areas according to latency. In Table III, we compared the estimated result of each channel $y1$-$y19$ with previous results shown in Table I [8]. Coincident areas are shown in Table III.

Some coincident results using the one-dipole ECDL method were found and are also shown in TABLE III.

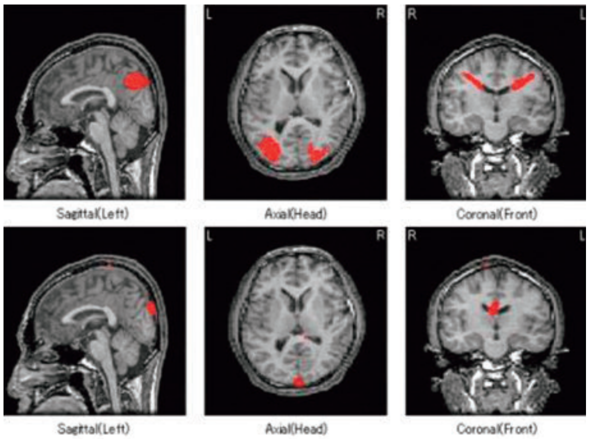

Figure 4　Two Cases of estimated ECDs using the one-dipole ECDL method: Dispársed (Upper) and Concentrated (Lower) ECDs.

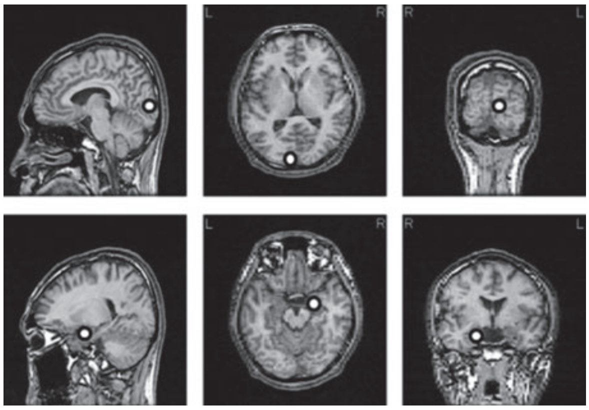

Figure 5　Example of estimated ECDs using the three-dipole ECDL method.

VI. Discussion

In the present study, we compared results from an ECDL three-dipole method to single-trial EEG data, after applying ICA, with results using a similar ECDL method to ERPs.

As shown in TABLE III, our estimated results were almost identical with that of our previous research. However, the new estimated results different in that there were brain areas that were lost in our previous ERP data analyses.

We conclude that ICA is effective as a pre-processing method for estimation using ECDL with a three-dipole model. Moreover, changing the latency range from 0–2000ms to 0–1000ms improved the results. These findings

TABLE II Relationship between Estimated ECD and Latency Using the First Component

Estimated Part	V1	R ITG	R ParaHip
Latency [ms]	128	None	374
R AnG	Wernicke	R Broca	R ParaHip
None	None	None	510
R PstCG	L FuG	R ParaHip	Broca
None	None	595	None

TABLE III Estimated Areas and Latencies Using the ECDL Method for the 19ch Component Data

Estimated Part	V1	R ITG	R ParaHip
Latency [ms]	y1: 128 y2: 129 y7: 141 y8: 124	y3: 325 y12: 318 y17: 326 y18: 310	y1: 374 y2: 394 y6: 393 y7: 384 y8: 389 y13: 404 y15: 402 y16: 386
R AnG	Wernicke	R Broca	R ParaHip
y3: 427 y13: 430	y12: 451 y16: 448 y19: 439	y9: 484 y10: 484 y18: 488	y1: 510
R PstCG	L FuG	R ParaHip	Broca
y7: 505 y9: 530	y8: 558 y10: 553 y17: 575	y1: 595 y12: 593 y16: 603	y3: 630 y8: 686 y16: 667

suggest that dividing the latency range more precisely may obtain better preprocessing results using ICA for the ECDL three-dipole method used here.

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