Estimation of Cortical Dipole Distributions for Multiple Signal Sources Based on ICA

Junichi Hori
Department of Biocybernetics
Niigata University
Niigata, Japan
hori@eng.niigata-u.ac.jp

Yoshiki Watanabe
Graduate School of Science and Technology
Niigata University,
Niigata, Japan

***Abstract*—Cortical dipole imaging is one of the spatial enhancement techniques from the scalp electroencephalogram. We investigated the cortical dipole imaging for multiple signal sources under time-varying non-uniform noise conditions. The effects of incorporating statistical information of noise into the spatiotemporal inverse filter were examined in three sphere volume conductor model. The parametric projection filter that incorporated with noise covariance was applied to the inverse problem of EEG measurements. The noise covariance matrix was estimated by applying independent component analysis to the scalp potentials. The spatial filter was expanded to apply to the time-varying non-uniform noise conditions such as eye blink artifact. Moreover, multiple dipole distributions were introduced to extract individual signal sources. The proposed imaging technique was applied to human experimental data of visual evoked potentials.**

Keywords- EEG; cortical dipole imaging; spatial inverse filter; noise covariance; independent component analysis; multiple sources

I. INTRODUCTION

It is important to develop high resolution imaging techniques to enhance the spatial resolution of EEG. Among the approaches to correct the smearing effect, of interest is the spatial enhancement approaches, which attempt to deconvolve the low-pass spatial filtering effect of volume conduction of the head [1]-[8]. Equivalent dipole imaging has been proposed to estimate the high-resolution cortical dipole distribution to account for the scalp potential [1], [2], [7]. In this model, the electrical sources inside of the brain are equivalently represented by the signal distribution on the dipole layer in high spatial resolution. The cortical dipole imaging requires solving an inverse problem described by the transfer function from the scalp potentials to the dipole layer. We have developed an inverse procedure for cortical dipole imaging using a parametric projection filter (PPF) which enables estimation of inverse solutions in the presence of noise information [9], [10]. Information related to noise distribution, as defined by the covariance matrix, was assumed to be known. Our previous results indicated that the PPF provided a better approximation to the original dipole distribution than that of traditional inverse techniques such as Tikhonov regularization and truncated singular value decomposition in the case of low correlation between signal and noise distributions [9], [10].

In order to accomplish the high-resolution brain functional imaging using the PPF, it is necessary to estimate the noise components in accuracy. In clinical and experimental settings, the noise covariance might be estimated from data that are known to be source-free, such as pre-stimulus data in evoked potentials [11], [12]. However, it was difficult to distinguish the noise from EEG data. As another method, the noise covariance matrix was estimated from the noise components which were separated by applying independent component analysis (ICA) [13] to the observed EEG signals [14]. ICA extracts independent sources from the observed signal based on statistical independence of the original signal. We supposed that the signal and noise are independent of each other. In order to estimate the noise covariance, it was investigated that how to extract the noise component from EEG signals. The simulation results suggested that the PPF provided excellent performance when the noise covariance was estimated from the differential noise between the observed EEG signal and the separated signal using ICA [14]. Moreover, the spatial resolution of the cortical dipole imaging was improved while the influence of noise was suppressed by adjusting the duration of noise sample according to the signal to noise ratio.

Actually, the electrical activity of the brain is fluctuated in both spatial and temporal domains. In addition, multiple signal sources simultaneously exist inside of the brain. Moreover, the signal to noise ratio of the scalp potential measured by distributed electrodes varies because of the variance of electrode impedances or the measuring environment. The scalp potentials are also influenced by the time-varying non-uniform noise such as eye blink artifacts or body movements. In this study, the proposed ICA-based inverse filter was expanded to the spatiotemporal inverse filter to apply to time-varying non-uniform noise conditioning. Moreover, to extract each signal source, new imaging method of multiple dipole distributions was proposed using the noise covariance matrix for each signal source. The noise covariance matrix was estimated by assuming the other signal and noise components as noise to obtain the dipole distribution for one signal component. The proposed method was examined by computer simulations and experimental study.

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II. Methods

A. Cortical Dipole Imaging

In this study, the head volume conductor was approximated by an inhomogeneous three-concentric sphere model [6]. Dipoles are uniformly distributed over a sphere inside of the brain. This model incorporates variation in conductivity of different tissues such as the scalp, the skull, and the brain. An equivalent dipole layer within the brain simulates the brain electrical activity without *ad hoc* assumption on the number and the orientation of source dipoles. The transfer matrix from the dipole layer to the scalp potential is obtained by considering the geometry of the model and the physical relationships among the quantities involved. The dipole layer distribution is reconstructed from the recorded scalp potential by solving an inverse problem of the transfer matrix.

The scalp potential distribution measured by scalp surface electrodes is defined by $\mathbf{g} = \mathbf{A}\ \mathbf{f} + \mathbf{n}$ where $\mathbf{f}$ is the vector of the equivalent dipole sources distributed over the dipole layer and $\mathbf{n}$ is the additive noise. $\mathbf{A}$ represents the transfer matrix from the equivalent dipole sources to the scalp potential signals. It is important to infer the origins from the recorded EEG and to map the sources that generate the scalp EEG. Thus, the dipole source distribution $\hat{\mathbf{f}}$ is estimated by $\hat{\mathbf{f}} = \mathbf{B}\ \mathbf{g}$ where $\mathbf{B}$ is the inverse filter. Because the number of measurement electrodes is always much smaller than the dimensions of the unknown vector $\hat{\mathbf{f}}$, this problem is an underdetermined inverse problem.

B. Spatial Inverse Filter

Several inverse techniques have been proposed to solve such inverse problems. The PPF, which allows estimating solutions in presence of information on noise covariance structure, has been introduced to solve the inverse problem [9], [10]. The PPF is given by

$$\mathbf{B} = \mathbf{A}^{\mathrm{T}}\ (\ \mathbf{A}\mathbf{A}^{\mathrm{T}} + \gamma \mathbf{Q}\ )^{-1} \tag{1}$$

where γ is a positive number known as the regularization parameter and $\mathbf{A}^{\mathrm{T}}$ the transpose matrix of $\mathbf{A}$. The matrix $\mathbf{Q}$ is the noise covariance derived from the expectation over the noise ensemble $\mathrm{E}[\mathbf{n}\ \mathbf{n}^{\mathrm{T}}]$. The regularization parameter γ controls the mutual weights of two terms. The determination of the value of parameter γ is left to the subjective judgment of the user. A criterion that estimates the optimum parameter using iterative calculation was used for restoration [9]. The criterion estimates the parameter that minimizes the approximated error between the original and estimated source signals without knowing the original source distribution.

The noise covariance matrix has to be estimated to construct the PPF. If we can obtain the time-varying noise component $n_i(t)$ on the electrode number i, each element of the matrix $\mathbf{Q}$ at the time instant t' is approximated from

$$Q_{i,j}(t') = \frac{1}{T} \sum_{t=t'-T/2}^{t'+T/2} \{ n_i(t) - \mu_i \}\ \{ n_j(t) - \mu_j \} \qquad (i, j = 1, 2, \ldots, K) \tag{2}$$

where μ_i is the temporal average of $n_i(t)$, K is the number of electrodes, T is the duration of sampled noise, and t' is the time at the center of the duration. The noise covariance should be changed according to the signal and noise conditions. In the present study, the noise covariance was estimated to adjust for each time instant and for each signal source. We estimated the noise covariance using ICA as described in next section. If the signal covariance can be obtained, the PPF would be expanded to the parametric Wiener filter incorporating the signal and noise covariance matrices.

C. Independent Component Analysis

The PPF in Eq. (1) requires the noise covariance. However, the signal and noise components are intermingled in the observed EEG signals. In such cases, each component was separated by ICA, which extracts independent sources from the observed signal based on statistical independence of the original signal. FastICA algorithm was used for performing the estimation of ICA [13]. This algorithm is based on a fixed-point iteration scheme maximizing non-Gaussianity as a measure of statistical independence. Non-Gaussianity was measured using an approximation of negentropy. The outline of ICA algorithm is as follows:

Suppose the observed signals were described by a mixing matrix and independent sources. First, the number of sources is decided using principle component analysis (PCA). In the PCA, the order of EEG signals is reduced to the number of independent components. The order was decided by considering the contribution ratio of the eigen values of the signal and the anatomical knowledge of the distributions of the sources. The principle component is derived using a whitening matrix that serves to reduce the dimensionality of the matrix. Next, the independent signals are estimated using the appropriate restoring matrix. Finally, the original signal is estimated by applying the restoring matrix to principle components. An inverse of the mixing matrix is described by multiplying a whitening matrix and a restoring matrix.

D. Spatial Inverse Filters for Multiple Sources

ICA was applied to EEG signals in order to extract the independent components as shown in Fig. 1. These components were separated into the signal and the noise components according to a priori physiological information. The number of independent components and signal and noise components were empirically estimated from the anatomical knowledge of the spatiotemporal distributions of separated components. Thus, we obtained the separated signal and noise components, $\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N, \mathbf{n}_1, \mathbf{n}_2, \ldots, \mathbf{n}_M$ by applying a mixing matrix. Here, $\mathbf{s}_i$ ($i = 1, 2, \ldots, N$) and $\mathbf{n}_i$ ($i = 1, 2, \ldots, M$) is the signal and noise components, respectively and N and M is the number of signal and noise, respectively.

From the results of the previous study [18], to improve the restorative ability, the noise covariance matrix was estimated from the differential noise between the original EEG signal and the separated signal using ICA. That is, the components without the signal component were assumed as noise. If the number of the dipole sources is more than one, each signal

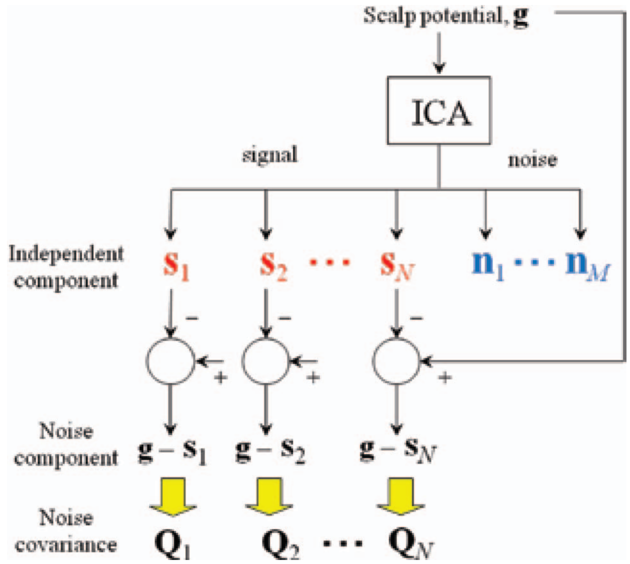

Fig. 1. Estimation of noise covariance matrices incorporated with the inverse filters. Separated signal and noise components with ICA were used for noise covariance calculation.

component may be separately extracted from the mixed EEG signals. Moreover, the inverse filter should be optimized for each signal source component. To accomplish this aim, the differential noises $\mathbf{n'}_i$ (i = 1, 2, ..., N) were calculated for each dipole sources: $\mathbf{n'}_i = \mathbf{g} - \mathbf{s}_i$. Thus, the noise covariance matrix was calculated by $\mathbf{Q}_i = E[\mathbf{n'}_i \mathbf{n'}_i^T]$. The spatial inverse filter for each signal sources was designed using this noise covariance matrix for high resolution cortical dipole imaging. Thus, we estimated several cortical dipole distributions for each dipole sources. The estimated dipole distribution for single source $\mathbf{s}_i$ is derived by

$$\hat{\mathbf{f}}_i = \mathbf{B}(\mathbf{Q}_i)\,\mathbf{g} \tag{3}$$

These distributions would extract one dipole source while the other dipole sources and the noise are reduced.

III. Results

A. Simulations

In the inhomogeneous spherical source-conductor model, the radii of the brain, the skull, and the scalp spheres were taken as 0.87, 0.92, and 1.0, respectively [6]. The normalized conductivity of the scalp and the brain was taken as 1.0, and that of the skull as 0.0125. The potentials on the scalp surface, generated by current dipoles inside the brain, can be calculated by solving the forward problem from the dipole source to the scalp-surface potential. 128 electrodes uniformly distributed over the upper hemisphere were used in the simulation. The scalp potentials were contaminated with uniform Gaussian white noise (GWN) or time-varying non-uniform noise. The noise level was set to 0.1. A dipole layer with 1280 radial dipoles at a radius of 0.8 was used [7]. We examined the restorative ability of the PPF under various signal and noise conditions. The estimating results were evaluated using the relative error between actual and estimated dipole layer distributions and maps of the dipole distribution.

In the primary simulation, single dipole source was used to simulate the time-varying signals under the condition of time-varying non-uniform noise. The radial dipole source was located at the elevation 20 degrees of posterior side with the eccentricity of 0.6. The strength of the dipole changed as sin wave with the frequency of 13 Hz. Two radial dipole sources located at the frontal lobe were assumed as the eye-blink artifact. Uniform GWN was also added to the scalp potential. Data was collected for 0.6s with a sampling rate of 1 kHz. Scalp potential distributions with or without the artifact and the estimated distributions are shown in Fig. 2. The order of ICA was estimated to be 2 from the contribution ratio of the eigen values in EEG. The scalp potential was faded with low conductivity of the skull. Especially, the scalp potential in right map was contaminated with eye blink artifact. Two kinds of noise covariance were calculated using the differential noises including the artifact or not. In the case of imaging without the artifact in left map, when the duration was set to 40ms the signal was localized to occipital lobe. In the case of imaging with noise, when the duration was set to 100ms, the artifact was eliminated while the signal was localized at occipital lobe. From these results, the noise duration for noise covariance calculation should be adjusted for optimum dipole imaging. It was considered that if the signal is noisy, the duration should be extended.

Next, two dipole sources were used to represent multiple localized brain electrical sources. The radial dipole sources were located at left occipital and right parietal lobes with the eccentricity of 0.7. The strength of each dipole was changed with sinusoid in time. The frequencies of fluctuation in the dipole moments were set to 12 Hz and 20 Hz that assuming EEG alpha and beta activities, respectively. The scalp potential was contaminated with 10% GWN (Fig. 3). The mappings were illustrated at the viewpoint from the back of the head. The number of independent signal sources was estimated as two. Thus, two noise components, that is, the differential noise between the scalp potential and the separated signal 1 ($\mathbf{g}-\mathbf{s}_1$) and the differential noise between the scalp potential and the separated signal 2 ($\mathbf{g}-\mathbf{s}_2$) were calculated for noise covariance. In the scalp potential, the signal at the right hemisphere was hidden because of the strong signal at the left hemisphere. The dipole distributions for two dipole sources were estimated with two difference noises. The dipole distribution for the separated signal 1 was localized at the left occipital lobe with 20ms of noise duration. On the other hand, the dipole distribution for the separated signal 2 was localized at right temporal lobe with 70ms noise duration. The results indicated that the spatial inverse filters should be adjusted to the individual signal sources using the noise covariance matrix in order to extract each signal source from multiple sources. Moreover, the hidden signals could be extracted by adjusting the noise

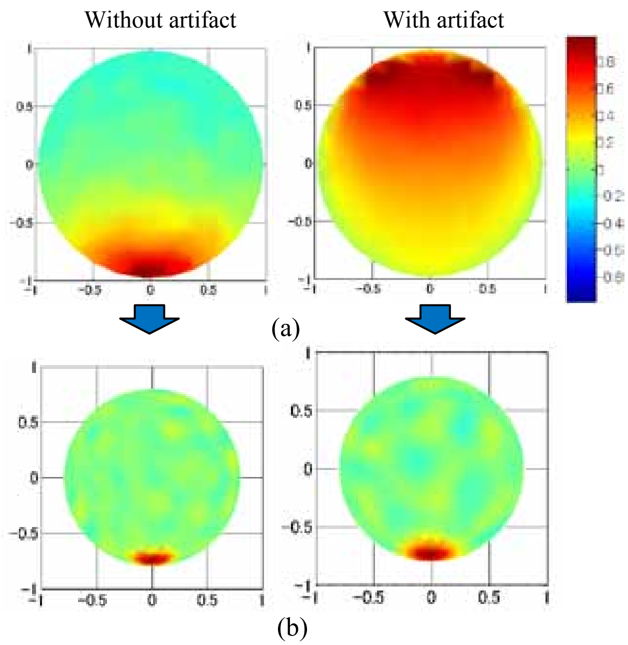

Fig. 2. Estimation results of dipole distributions with or without artifact. (a) Scalp potentials, (b) Estimated dipole distributions.

duration.

B. Human Experiments

Human visual evoked potential (VEP) experiments were carried out to examine the performance of the proposed method. One healthy subject was studied in accordance with a protocol approved by the Institutional Review Board of the University of Illinois at Chicago. Visual stimuli were generated by the STIM system (Neuro Scan Labs, Inc.). 96-channel VEP signals referenced to right earlobe were amplified with a gain of 500 and band-pass filtered from 1 Hz to 200 Hz by Synamps (Neuro Scan Labs, Inc.), and were acquired at a sampling rate of 1 kHz by using SCAN 4.1 software (Neuro Scan Labs, Inc.). The electrode locations were measured using Polhemus Fastrack (Polhemus, Inc.) and best fitted on the spherical surface with unit radius. Half visual field pattern reversal check boards (black and white) with reversal interval of 0.5s served as visual stimuli and 400 reversals were recorded to obtain averaged VEP signals. Positive peak was observed around 80ms after visual stimuli (P100). The cortical dipole imaging was applied to P100. The order of ICA was estimated to be 2 from the contribution ratio of eigen values of the EEG. From the results of ICA, the amplitudes of independent components were localized at the occipital lobe. Two kinds of difference noise were calculated for noise covariance. Fig. 4 shows the results of the estimated inverse solutions of cortical dipole distribution for visual evoked potential (VEP) at around 80ms after visual stimuli, that is to say P100. The maps show the dipole distributions observed from the posterior side of 30 degrees in elevation. The noise covariance was calculated with various duration of noise sample around the imaging time. As

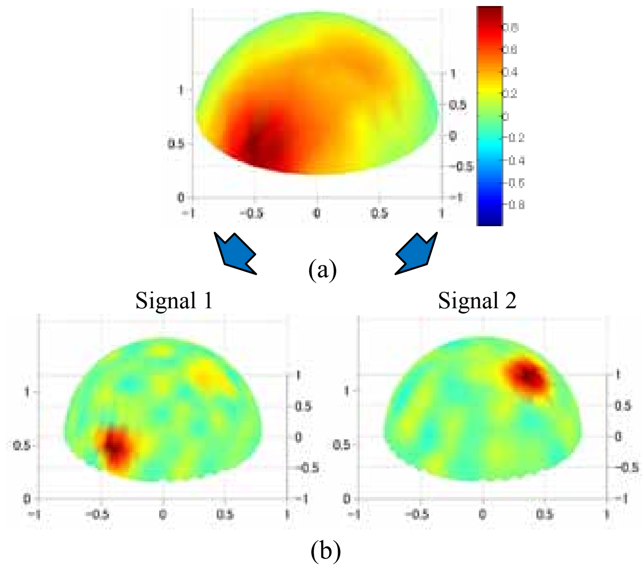

Fig. 3. Estimation results of dipole distributions in the case of two dipole sources. (a) Scalp potential, (b) Estimated dipole distributions.

compared with the scalp potential in Fig. 4(a), the estimated dipole distribution performed well. Especially, the signal was localized at the left occipital lobe with 10ms of noise duration and at right the occipital lobe with 60ms of noise duration. The maps demonstrated the localized area around the visual field with less noise.

IV. Discussion

We introduce the PPF for the inverse problem of cortical dipole imaging. The PPF requires the statistical noise information described by the covariance. We examined the estimation methods based on ICA for the noise covariance matrix. Our estimation method provided the signal and noise components even if they are mixed with each other. In order to extract the noise component, it is necessary to remove signal components. Therefore, the accuracy of signal separation using ICA exercises a great influence on the precision of the cortical dipole imaging. In general, the order of ICA was determined from the contribution ratio of the eigen values. The order of ICA should be higher than or equal to the number of signal sources. However, the actual signal and noise components are unknown in clinical application and the number of the dipole sources may change depending on time. We checked the accuracy of signal and noise separation from the amplitude and the distribution of separated independent components referring to an anatomical knowledge.

From the results of the previous study [14], it was better to use the differential noise between the EEG signal and the separated signal for calculating the noise covariance matrix in the PPF rather than the separated noise. Moreover, the noise components for covariance should be sampled to include the time instant of the imaging and the duration of noise sample should be adjusted according to the signal and noise

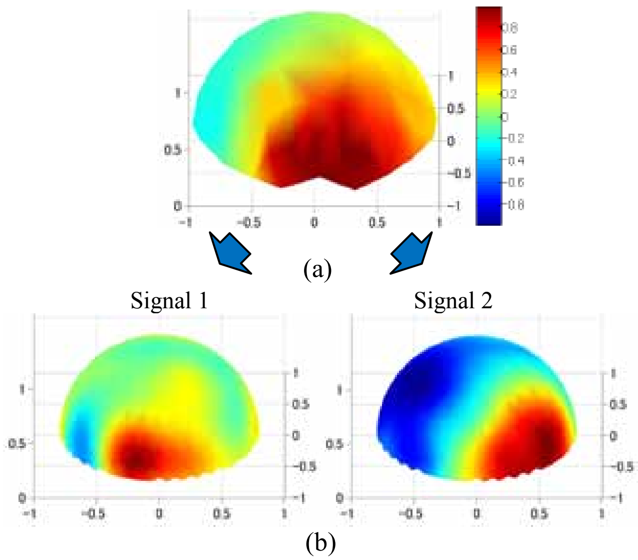

Fig.4. Estimated results of dipole distributions for VEP.
(a) Scalp potential, (b) Estimated dipole distributions.

conditions. In the present simulation study, when the EEG signal was noisy, the duration of noise sample should be set to long. Otherwise, the signal is in less noise, the duration should be set to short to localize the dipole distribution. Thus, the duration of noise samples should be adjusted for optimum calculation of noise covariance according to the signal to noise conditions. Here, the signal represents a signal component to be extracted and the noise represents both other signal components and noise components.

When the amplitudes of the multiple signals are extremely different each other, weak signals are hidden in strong signals. Thus, in the present research, we proposed the individual imaging method of the dipole distributions for each signal source. The visualization was carried out by the several spatial inverse filters with appropriate noise covariance matrices. In this method, the signals except the attended signal were assumed as the noise. Thereby, the weak signal can also be visualized by the proposed method.

The proposed method was applied to clinical data of the VEPs based on the above-mentioned results. The number of signal source was estimated as two from the results of the ICA. The tendency of the experimental results by changing the duration of noise sample were the same as that of the computer simulations. Since the obtained result was in good agreement with a physiological knowledge, it is expected that the proposed method will be applicable to actual EEG signals. However, when the signal to noise ratio was small, long duration is needed for signal extraction. As a result, the signal was faded. It is considered to be improved by using the parametric Wiener filter.

Further investigations using a more realistic head conductor model and experimental data are necessary to validate the performance of the proposed model in cortical dipole source localization.

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