Auditory Evoked Fields Analysis Using EMD and ICA

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***Abstract*—The empirical mode decomposition (EMD) is a time-frequency analysis method for analyzing the nonlinear and non-stationary biomedical data which combined with the independent component analysis (ICA) approach allows for more powerful source noise reduction. This paper presents a novel technique for decomposing and localizing the magnetoencephalographic (MEG) data with auditory evoked fields (AEFs) experiment based on EMD and ICA associated with the source localization technique. Applying our technique to the unaveraged single-trial AEFs data, we demonstrate the simulation results.**

***Index Terms*—empirical mode decomposition (EMD), intrinsic mode function (IMF), independent component analysis (ICA), magnetoencephalographic (MEG)**

I. Introduction

Magnetoencephalographic (MEG) is noninvasive monitoring techniques for measuring human brain activity with a high temporal resolution. MEG-detected magnetic field is originally generated by the intercellular or extracellular currents of neurons. The motivation for studying MEG is to extract the essential features of measured data and represent them as corresponding human brain functions. Since the magnetic field of a brain signal is relatively weak in the MEG experiment, the spontaneous and environmental noise usually effects the recorded data.

To remove or reduce the spontaneous and environmental noise or to identify the behavior and location of interesting activities such as evoked responses, the most widely used and reliable method is to take an average across multi-trial data sets. Moreover, to visualize the dynamics of brain activity, a robust data analysis method for decomposing and localizing the unaveraged single-trial MEG data based on the independent component analysis (ICA) approach has been developed [1], [2]. Considering the nonlinear and nonstationary features of biomedical data sets, the empirical mode decomposition (EMD) method has been developed [4], and was applied to extract the essential features of multi-channel EEG data [6].

In this paper, we propose a three-staged technique to the unaveraged single-trial MEG data based on the EMD method associated with the ICA approach and the source localization technique. In the first stage, we apply the joint approximate diagonalization of eigenmatrices (JADE) algorithm [3] associated with the factor analysis (FA) method to reduce the power of additive noise and decompose independent components. In the second stage, the EMD method is used to decompose the individual independent component into a finite and usually a small number of IMF components. Then we combine the desirable components which are obtained from the decomposed IMFs. In the third stage, the combined signal is projected into the sensor space, and the source localization technique is applied to find location of dipoles based on the standard patio-temporal fitting routine. Applying the proposed technique to the unaveraged single-trial AEFs data, we demonstrate the simulation results.

II. Method of Data Analysis

A. Independent component analysis

This subsection presents applying the ICA approach based on the JADE algorithm [3] associated with the FA method to decompose the observed data into the independent components [1]. ICA is a powerful statistical tool for extracting independent components given only observed data that are mixtures of unknown sources.

Based on the principle of MEG experiment, the AEFs dataset can be formatted in a data matrix form as

$$\mathbf{X}_{(m\times N)} = \mathbf{A}_{(m\times n)}\mathbf{S}_{(n\times N)} + \mathbf{E}_{(m\times N)}, \tag{1}$$

where N denotes data samples. When the sample size N is sufficiently large, the covariance matrix of the data can be written as $\mathbf{\Sigma} = \mathbf{A}\mathbf{A}^T + \mathbf{\Psi}$, where $\mathbf{\Sigma}= \mathbf{X}\mathbf{X}^T/N$, and the covariance of noise components $\mathbf{E}$ represented by $\mathbf{\Psi} = \mathbf{E}\mathbf{E}^T/N$ is a diagonal matrix. For convenience, we assume that $\mathbf{X}$ has been divided by $\sqrt{N}$ so that the covariance matrix can be given by $\mathbf{C} = \mathbf{X}\mathbf{X}^T$.

To estimate both matrix $\mathbf{A}$ and the diagonal elements of $\mathbf{\Psi}$ from the data, we employ a cost function as

$$L(\mathbf{A},\mathbf{\Psi}) = tr\left[\mathbf{A}\mathbf{A}^T - (\mathbf{C}-\mathbf{\Psi})\right]\left[\mathbf{A}\mathbf{A}^T - (\mathbf{C}-\mathbf{\Psi})\right]^T. \tag{2}$$

Minimizing the cost function, we obtain an estimate $\hat{\mathbf{\Psi}}$ such as $\hat{\mathbf{\Psi}} = Dag(\mathbf{C} - \hat{\mathbf{A}}\hat{\mathbf{A}}^T)$. The estimate for $\hat{\mathbf{A}}$ can be obtained from $\frac{\partial L(\mathbf{A},\mathbf{\Psi})}{\partial \mathbf{A}} = 0$. Here, we employ eigenvalue decomposition $\hat{\mathbf{A}} = \mathbf{U}_n\mathbf{\Lambda}_n^{\frac{1}{2}}$, where $\mathbf{\Lambda}_n$ is a diagonal matrix whose elements are the n largest eigenvalues of $\mathbf{C}$. The columns of $\mathbf{U}_n$ are the corresponding eigenvectors.

Once the estimates for $\hat{\mathbf{A}}$ and $\hat{\boldsymbol{\Psi}}$ converge to stable values, we can finally compute the score matrix using

$$\mathbf{Q} = \left[\hat{\mathbf{A}}^T \hat{\boldsymbol{\Psi}}^{-1} \hat{\mathbf{A}}\right]^{-1} \hat{\mathbf{A}}^T \hat{\boldsymbol{\Psi}}^{-1}. \tag{3}$$

From the above result, the new transformation data can be obtained by employing $\mathbf{z} = \mathbf{Q}\mathbf{x}$.

The rotation procedure in JADE uses matrices $\mathbf{F}(\mathbf{M})$ formulated by a fourth-order cumulant tensor of the outputs with an arbitrary matrix $\mathbf{M}$ as

$$\mathbf{F}(\mathbf{M}) = \sum_{k=1}^{K} \sum_{l=1}^{L} \mathrm{Cum}(z_i, z_j, z_k, z_l) m_{lk}, \tag{4}$$

where $\mathrm{Cum}(\cdot)$ denotes a standard cumulant and m_{lk} is the (l,k)-th element of matrix $\mathbf{M}$. The correct rotation matrix W can be obtained by diagonalizing the matrix $\mathbf{F}(\mathbf{M})$; namely, $\mathbf{W}\mathbf{F}(\mathbf{M})\mathbf{W}^T$ approaches to a diagonal matrix. After the ICA approach, the decomposed independent components $\mathbf{y} \in \mathbf{R}^n$ can be obtained from a linear transformation as

$$\mathbf{y}(t) = \mathbf{W}\mathbf{z}(t), \tag{5}$$

where $\mathbf{W} \in \mathbf{R}^{n \times n}$ is also termed as the admixing matrix.

B. Empirical mode decomposition

The EMD method as a time-frequency analysis tool for nonlinear and nonstationary signals has been proposed in [4]. EMD is a fully data driven technique with which any complicated data set can be decomposed into a finite and often small number of Intrinsic Mode Functions (IMF).

An IMF component as a narrow band signal is a function defined having the same numbers of zero-crossing and extrema, and also having symmetric envelopes defined by the local maxima and minima respectively.

The procedure to obtain the IMF components from an observed signal is called sifting [4] and it consists of the following steps:

1) Identification of the extrema of an observed signal waveform y_k(t).
2) Generation of the waveform envelopes by a cubic spline line through connecting local maxima as the upper envelope and local minima as the lower envelope.
3) Computation of the local mean $av_1(t)$ by averaging the upper and lower envelopes.
4) Subtraction of the mean from the data for a primitive value of IMF component as $h_1(t) = y_k(t) - av_1(t)$.
5) Repetition step 1)-4) q times, until $h_q(t)$ is an IMF component, $h_{q-1}(t) - av_q(t) = h_q(t)$.
6) Designation the first IMF component as $c_1(t) = h_q$(t) from the data, so that the residue component is $r_1(t) = y_k(t) - c_1(t)$.
7) Repetition step 1)-6) u times, the residue component contains information about longer periods which will be further resifted to find additional IMF components, by $r_u(t) = y_k(t) - \sum_{i=1}^{u} c_i(t)$.

The sifting algorithm is applied to calculate the IMF components based on a criterion by limiting the size of the standard deviation (SD) computed from the two consecutive sifting results as

$$\mathrm{SD} = \sum_{t=0}^{T} \left[\frac{(h_{q-1}(t) - h_q(t))^2}{h_{q-1}^2(t)} \right]. \tag{6}$$

in which a typical value for SD can be set between 0.2 and 0.3 for the sifting procedure.

Based on the sifting procedure for one channel of the MEG data, we finally obtain

$$y_k(t) = \sum_{i=1}^{u} c_i(t) + r_u(t). \tag{7}$$

In Eq. (7), $c_i(t)(i = 1, \cdots, u)$ represents u IMF components, and r_u represents a residual component which can be either a mean trend or a constant. Since each IMF component has a specific frequency, it is easily to discard high frequency such as 50 Hz electrical power interference after raw data decomposition. The rest desirable components are combined to a new signal $y'_k(t)$.

C. Source localization

After applied the ICA approach and EMD method, the level of noise has been reduced, and the independent component have been extracted from the observed data. To visualize the information of dipoles, the combined new signal is projected into the sensor space.

The virtual observation signals coming from the signal $y'_k(t)$ obtained as

$$\hat{\mathbf{x}}'(t) = \hat{\mathbf{A}}\mathbf{W}^{-1} \left[0 \cdots y'_k(t) \cdots 0\right]^T. \tag{8}$$

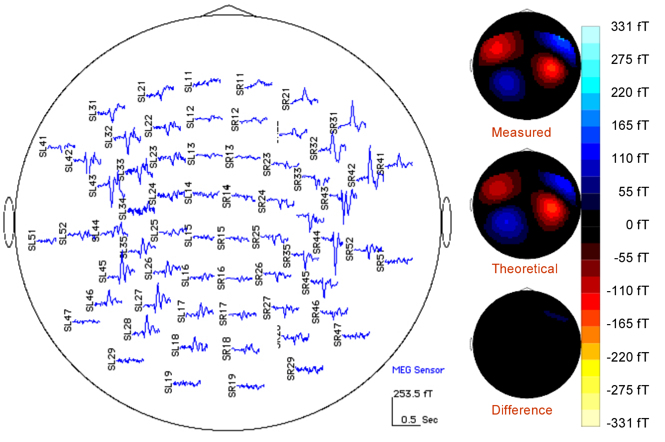
As an example, the map of $\hat{\mathbf{x}}'(t)$ corresponds to the 'measured' map (see, for example, Fig. 1).

III. Experimental Results

A. AEFs experiment

The AEFs data were recorded by using an Omega-64 (CTF Systems Inc., Canada) whole-cortex MEG system at the National Institute of Bioscience and Human Technology, Tsukuba, Japan. The sensor (SQUID: superconducting quantum interface device) arrays consist of 64 channels. The AEFs experiment was performed on a normal male adult in whom both ears were stimulated by a 1 kHz tone. Data of 630 trials were recorded in 379.008 s. Each single-trial was carried out in 0.6016 s and the stimulus was given at 0.2 s. The sampling rate was 312.5 Hz and the number of samples was 188 for each trial. In the experiment, the model sphere was set at x = -0.38 cm, y = 0 cm, z = 5.35 cm and r = 7.3 cm. Where x, y, z is the coordinate in a three-dimensional coordinate system. As an example, Fig. 2 is the 341th single-trial data.

The result of taking an average across 630 trials is shown in Fig. 1(a). Applying the source localization routine for fitting the two dipoles, we obtain the averaged map shown in Fig. 1(b). In this example, the latency was set at 96 ms. This is



(a) (b)

Fig. 1. Result for averaged AEFs data. (a) Result of taking an average across 630 trials. (b) Dipole estimation for averaged data.

a typical result for an averaged AEFs analysis in which the two dipoles appearing in the left and right temporal regions of the head. It should be noted that the amplitude information appear in the color scale bar (the maximum evoked response is 331 fT) only represents the strength of averaged responses across 630 trials.

Beyond the behavior and location of the evoked response as in averaged data, we search for the information regarding the activity strength related to a stimulation trial and the dynamics of each evoked response. In this paper, we present the results obtained by applying the proposed technique to decompose the average single-trial AEFs data.

B. AEFs data analysis

Various average single-trial data sets have been analyzed by using the proposed algorithms described in Section II. As an example, we show some results for the behaviors of decomposed the 341th single-trial data in Figs. 3 and 4. The result shown in Fig. 3(a) is derived by using the ICA approach. In this result, one independent component (IC_2) may be related to the N100 evoked responses since it has a pick point at around 0.1 s. IC_4 may be an α-wave component since its frequency is about 10 Hz and no pick point appears at 0.1 s. IC_1 and IC_3 as the additive interference can be discarded.

With the prior knowledge about AEFs, we know high frequency interference such as 50 Hz electrical power is strong in the AEF data. Furthermore, for removing that kind of noise contains in the independent component IC_2, we used the EMD method. Four IMF components (see $c_1 \sim c_4$) and a residue component (see r_5) were obtained shown in Fig. 3(b). In this case, c_1 is regarded as electrical interference because of it being with high frequency. In addition, the residual component r_5 is useless. Three IMF components ($c_2 \sim c_4$) as useful components are synthesized to a new signal (see c_s). It is clear that the combined signal with a lower level noise. To determine the location and activity strength of neuronal sources, we project the signal c_s into the sensor space by using Eq. (8). The virtually observed signals with a smooth distribution on the nearby sensors are obtained in Fig. 4(a).

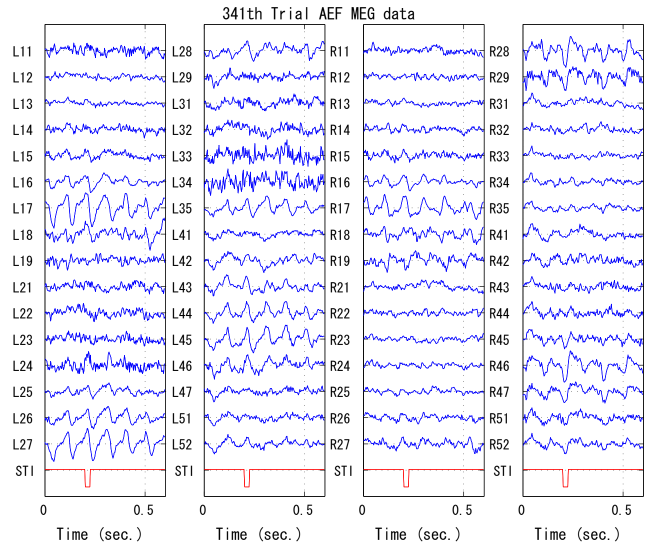
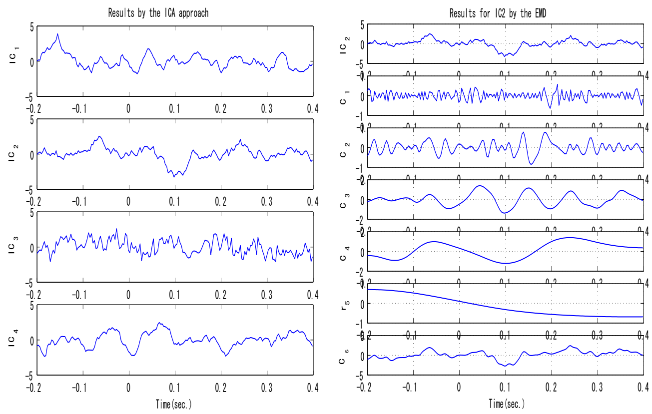
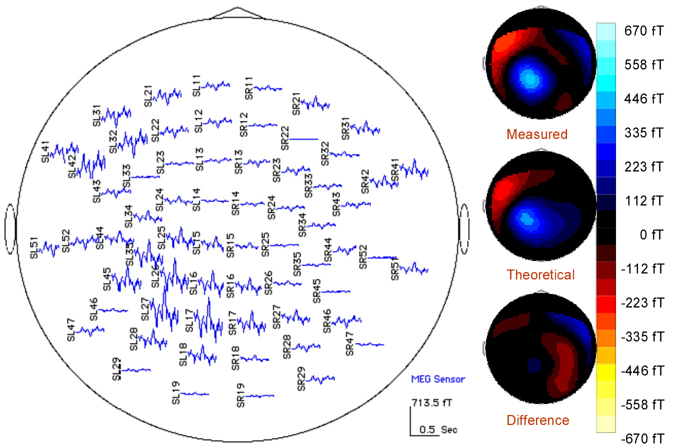


Fig. 2. 341th single-trial AEFs data (STI: stimulus given at 0.2s).



(a) (b)

Fig. 3. Results for the 341th single-trial data by the ICA approach and EMD method. (a) Independent components. (b) IMF components and residue.



(a) (b)

Fig. 4. (a) Result of projecting c_s to the sensor space. (b) Source localization (the left temporal source).

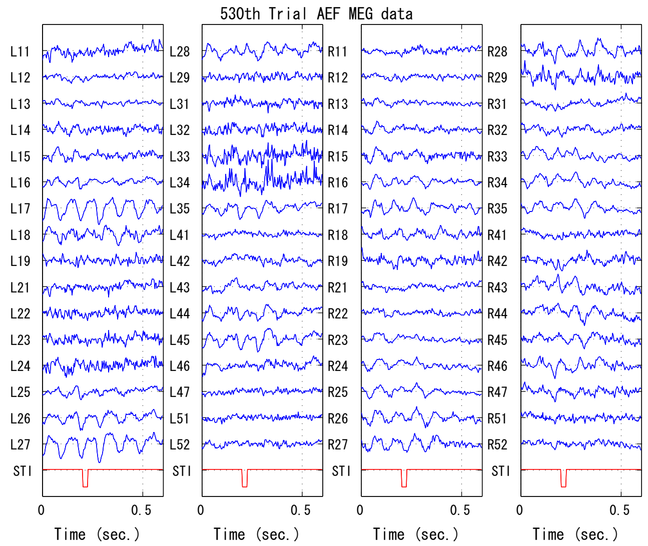
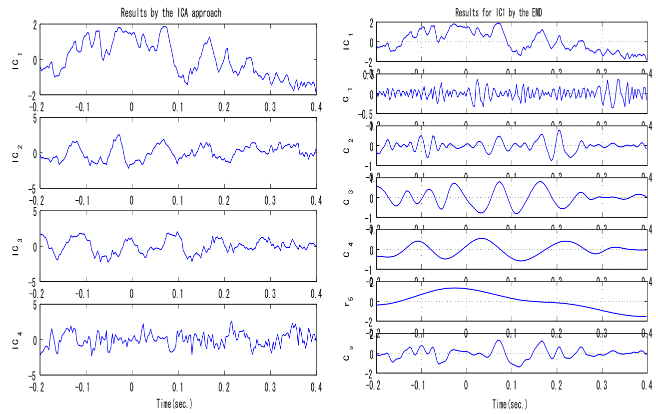
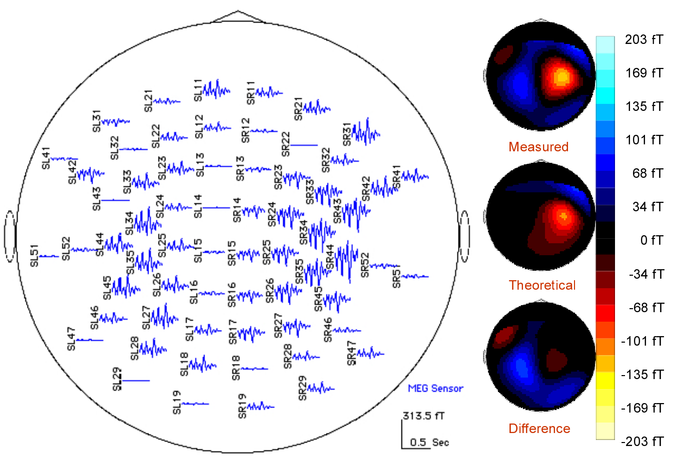


Fig. 5. 530th single-trial AEFs data (STI: stimulus given at 0.2s).



(a) (b)

Fig. 6. Results for the 530th single-trial data by the ICA approach and EMD method. (a) Independent components. (b) IMF components and residue.



(a) (b)

Fig. 7. (a) Result of projecting c_s to the sensor space. (b) Source localization (the right temporal source).

Then applying the standard patio-temporal dipole fitting routine to estimate the data (Fig. 4(a)), the result is obtained in Fig. 4(b). In this result, the map indicates that the magnetic field distribution for the combined c_s is in the left side of the temporal cortex. The 'Measured' map is derived from the combined component. The middle 'Theoretical' map is computed by moving a single dipole, and the bottom 'Difference' map denotes the estimation error between the 'Measured' and the 'theoretical' maps. In this case, we can note that the maximum amplitude is 670 fT.

Next, we show another example of applying the proposed technique to the 530th trial data in Figs. 6-7. In the Fig. 7(b), the map indicates that the magnetic field distribution for the combined c_s (see Fig. 6(b)) in the right side of the temporal cortex. In this case, we can note that the maximum amplitude is 203 fT. Comparing the results obtained by the proposed data analysis technique with the averaged results, we can conclude that the data analysis technique works efficiently even in a poor condition such as only using one single-trial observed data with a high level noise.

IV. Conclusions

In this paper, we proposed a technique based on the EMD method with the ICA approach and the source localization technique for analyzing the average single-trial AEFs data. We demonstrated several examples for analyzing the single-trial MEG data with AEFs experiment.

Through the analysis of unaveraged single-trial AEFs data by using our proposed technique, it is shown that the N100 evoked responses were extracted. These results were similar to the result by taking an average across 630 trials. We found also that the maximum amplitude is difference in each single-trial. The proposed algorithms are efficient for high level additive noise and high frequency noise. In further works, we will analyze other unaveraged single-trial AEFs data.

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