Elimination of Brain Noise from MEG Data using ICA with Robust Pre-Whitening Technique

Yoshio Konno (1), Jianting Cao (2,3), Tsunehiro Takeda (4), Hiroshi Endo (5), Mamoru Tanaka (1), and Takayuki Arai (1)

(1) Sophia University, Japan. (2) Saitama Institute of Technology, Japan. (3) RIKEN, Japan.
(4) Tokyo University, Japan. (5) National Institute of Bioscience and Human-Technology, Japan.

ABSTRACT

In this paper, single-trial and averaged multiple-trials data are analysed applying proposed robust pre-whitening technique with independent component analysis (ICA), in order to study the performance of source decomposition in each case. To evaluate the performance of source decomposition, we use a synthesized MEG data set. The main advantage of our data set is that dipole location of evoked responses and its dynamics are known in advance, which facilitates the evaluation of the decomposed components. Moreover, some existing ICA algorithms such as JADE, Fast-ICA, and Natural gradient-based ICA with robust pre-whitening technique are used to eliminate brain noise. Our results show the performance of source decomposition applying proposed approach and the effectiveness of JADE algorithm for our MEG data analysis.

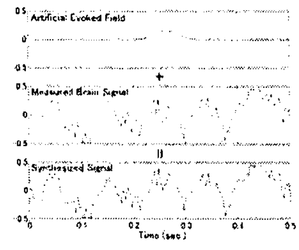

Figure 1. An example for data synthesizing.

KEY WORDS: Magnetoencephalography (MEG), robust pre-whitening technique, independent component analysis (ICA), JADE algorithm, fast-ICA, and natural gradient-based ICA, source localization.

INTRODUCTION

When detecting an MEG signal applying ICA, spontaneous and environmental noises may seriously affect recorded data because the magnetic field of brain signals is weak. The most widely used technique for reducing noises is to take averages across many stimulation trials. However, by taking averages, important information such as the trial-by-trial variation will be lost, making it advantageous to decrease the number of averages across data trials. The disadvantage of having fewer averages is that because SNR is very poor, the decomposition of a low-power source signal from recorded data is still influenced by noise. In this paper, we deal with both single-trial and averaged multiple-trials data, in order to study the accuracy of source decomposition in each case.

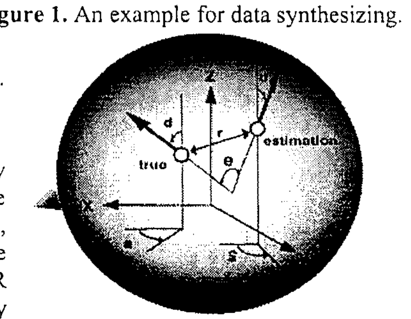

Figure 2. Distance and angle between true and estimated evoked fields.

MEG DATA SET

In this study, we use a synthesized MEG data set, which includes an artificial evoked field and real measured data (recorded by Omega-64). The behavior of our data set is similar to auditory evoked fields (AEFs). The sampling rate was 250 Hz with duration of 40 sec. and our data set was segmented into 80 trials. The source signals in this data set include evoked field response as well as the electrical power interference and the alpha-wave component involved in the real measured MEG data. The evoked field signal was artificially evoked from 0.2 to 0.3 sec. with a peak at 0.25 sec. (see Fig. 1). Dipole location, direction vector, and dipole moment of evoked field are set at [x, y, z]=[10, 10, 60] mm, [az, dec]=[50, 103] deg., and Q=40 (nAm), where a head model presupposes a sphere with a radius of 75 mm.

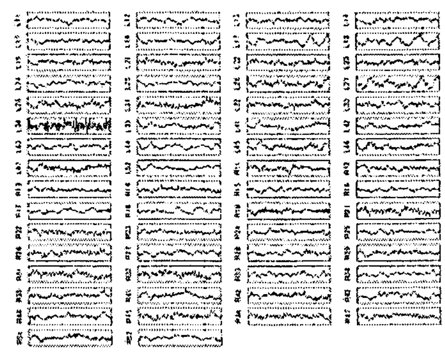

Figure 3. Averaged of 10 trials. The horizontal and vertical axes express time (0 - 0.5 sec.) and amplitude (-0.3 to 0.3 pT), respectively.

SIMULATION AND EVALUATION METHODS

In order to decompose brain sources, we apply the JADE [1], Fast-ICA [2], and natural gradient-based algorithm [3]. Moreover, we introduce our robust pre-whitening technique [4] for pre-processing. This technique is very capable of reducing the power of additive noises. A similar noise reduction approach that applies factor analysis to the decomposition of MEG data has been reported. Both this method and ours take additive noises into account, but with our robust pre-whitening technique, the distribution of additive noises is not restricted. Therefore, our technique is more robust and effective for data with non-Gaussian noises such as the outlier. In order to investigate the performance of source decomposition, we focus on: 1) the accuracy of source estimation, and 2) the power of decomposed components. In this study, we take averages across different numbers of trials from 1 to 50 trials, and in each averaging process, we use 30 moving samples.

To investigate the accuracy of source estimation, we apply dipole estimation to averaged observation and the decomposed evoked signal focusing on evoked response. Since dipole location and direction vector of evoked field were known in advance, the estimation error of evoked field can be obtained, comparing the true and estimated ones. We used the standard spatio-temporal dipole fitting routine, MEG v3.3a (CTF System Inc., Canada), to find the dipole. The distance between true and estimated source locations and the angle between true and estimated direction vectors, used for evaluation of source decomposition, are obtained as (see Fig. 2),

$$r = \left\{(x-\hat{x})^2 + (y-\hat{y})^2 + (z-\hat{z})^2\right\}^{1/2},\ \theta = \cos^{-1}\left\{\sin d \sin \hat{d} \cos(a-\hat{a}) + \cos d \cos \hat{d}\right\}. \quad (1)$$

In order to investigate the power of decomposed components, we take averages of the power of decomposed evoked field signal, electrical power interference, and alpha-wave component, in each number of averages.

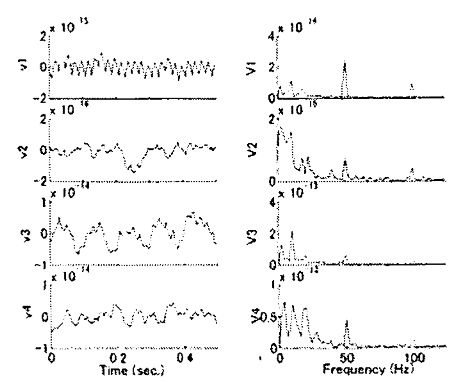

Figure 4. Result of source decomposition and its frequency contents.

P1-1

RESULTS

We first demonstrate the results of the source decomposition and localization, using the JADE algorithm, to the averaged 10 trials data as shown in Fig. 3. The results v(t) and the power spectra V(f) are shown in Fig. 4. Applying automatic classifying approach [5] to these decomposed components, v1, v2 and v3 in Fig. 4 are regarded as electrical power interference, evoked field response, and alpha-wave component, respectively. The estimated maps derived by averaged data and decomposed evoked response are shown in Fig. 5. Note that the evoked response appears on the left-front area of the brain. The estimated evoked field and the estimation error are shown in Tab. 1. Comparing the results of the JADE and taking averages, we conclude that estimated evoked field becomes more accurate by applying proposed approach.

Here, we demonstrate the performance of JADE, Fast-ICA, and natural gradient-based algorithm with robust pre-whitening technique. The accuracy of source estimation, the estimation error of evoked field calculated by Eq. (1), is shown in Fig. 6. Given these results, regardless of the analysis, the larger the number of averages, the lower estimation error becomes. Comparing the results of averaged data with decomposed evoked field, regardless of the number of averages, evoked field signal is accurately decomposed by applying any ICA algorithm. This means that estimated evoked fields derived by proposed approach are more accurate than those of taking averages and the number of average can be reduced by applying proposed approach.

The relationship between the power of each decomposed component and the number of averages is shown in Fig. 7. As for the power of electrical power interference and alpha-wave component, the larger the number of averages, the lower the power of these components become. This means that these components are influenced by taking averages. In contrast, the power of evoked response is not influenced by taking averages. The results of JADE algorithm especially appear to be stable against the number of averages. This means that JADE algorithm is very efficient for our data analysis. But, as for single-trial data analysis, the power of evoked field becomes very large, because of the influence of additive noise.

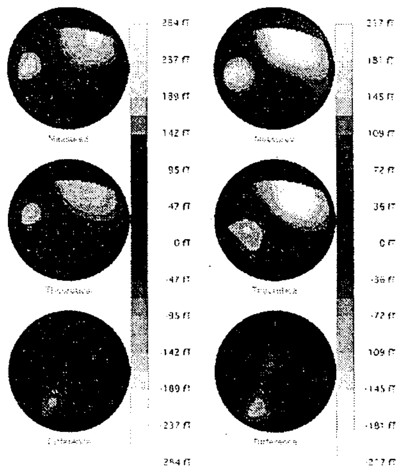

Figure 5. Estimated map focusing on evoked field: (left) averaged data, and (right) decomposed evoked field.

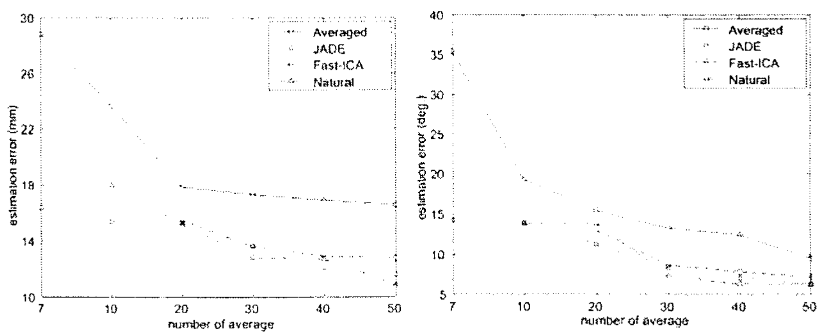

Figure 6. Estimation error applying JADE, Fast-ICA, and natural gradient-based algorithm: (left) dipole location, and (right) direction vector.

CONCLUSIONS

In this paper, the performances of source decomposition applying ICA with robust pre-whitening technique for single-trial and averaged MEG data are investigated. Besides, some existing ICA algorithms are used to eliminate brain noise from MEG data. Our results show the relationship between the accuracy of source decomposition and the number of averages, and applying our ICA approach, the number of average can be reduced. These results strictly confirmed the effectiveness of developed analysis methods.

REFERENCES

[1] J. F. Cardoso and A. Souloumiac, "Jacobi angles for simultaneous diagonalization," SIAM J. Mat. Anal. Appl., Vol. 17, No. 1, pp. 145-151, 1996.

[2] A. Hyvaerinen and E. Oja, "A fast fixed-point algorithm for independent component analysis," Neural Computation, Vol. 9, No. 7, pp. 1483-1492, 1997.

[3] S. Amari, A. Cichocki, H. H. Yang, "A new learning algorithm for blind signal separation," Advances in Newral Information Processing System 8, MIT Press, pp. 757-763, 1996.

[4] J. Cao, N. Murata, S. Amari, A. Cichocki and T. Takeda, "A robust approach to independent component analysis of signals with high-level noise measurements," IEEE Trans. on Neural Networks, Vol. 14, No. 3, pp. 631-645, June 2003.

[5] Y. Konno, J. Cao, T. Arai and T. Takeda, "Visualization of Brain Activities of Single-Trial and Averaged Multiple-Trials MEG Data," IEICE Trans. on Fundamentals, Vol. E86-A, No. 9, pp. 2294-2302, Sep 2003.

[6] S. Makeig, A. J. Bell, T. -P. Jung and T. J. Sejnowski, "Independent component analysis of electroencephalographic data," Advances in Neural Information Processing System 8, MIT press, pp.145-151, 1996.

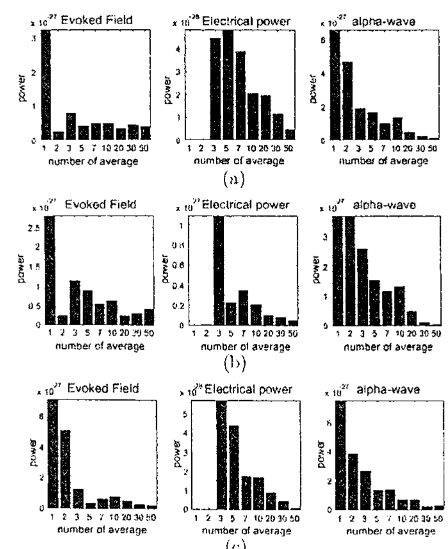

Figure 7. Power of decomposed components : (a) JADE, (b) Fast-ICA, and (c) natural gradient-based algorithm.

Table 1. Estimated map and estimation error.

	Dipole location (mm)				Direction vector (dec.)		
	x	y	z	r	az	dec	theta
True value	10.0	10.0	60.0	-	50.0	103.0	-
Before ICA	16.4	14.7	37.7	23.7	40.7	120.3	19.3
After ICA	-2.1	0.6	61.5	15.4	48.2	89.1	14.0