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A New Dynamical Approach to Auditory Evoked Magnetic Field by Blind Identification

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ABSTRACT

A new approach to understand neural dynamics underlying the generation of auditory evoked magnetic field is proposed. MEG time series data are temporally decorrelated by using a blind signal separation method. Two components are selected from their periodical property and a remixing matrix is applied to the two selected components to retrieve MEG signals of auditory evoked magnetic field. After principal component data for each sensor pairs are calculated, a minimum phase innovation model is identified from the viewpoint of statistical inverse problem. By using a blind identification method based on feedback system theory transfer functions can be evaluated to get a dynamical understanding of brain auditory functions. It is reported that all changes of their impulse responses between right and left hemisphere decay within about 40 ms, and that directional differences in transfer functions can be found.

KEY WORDS

Magnetoencephalogram, Auditory evoked magnetic field, Blind identification, Blind signal separation, Feedback system, Transfer function, Impulse response

INTRODUCTION

A new approach to understand neural dynamics underlying the generation of auditory evoked magnetic field (AEF) is proposed, in which we use a method of blind identification of transfer functions (TFs) based on feedback system theory as mentioned in [Kishida, 1996] [Kishida, 2003A]. In conventional MEG analysis [Hämäläinen, 1993], averaged waveforms have been used to investigate cortical representation of the human cognitive processes. However, MEG time series data contain more dynamic properties. In particular, dynamic information of cooperative activities between regions could be extracted. In the present paper, in addition to the averaged waveforms (the first moment of the MEG time series data), the second moment, namely, the correlation functions between the MEG SQUID channels, are analyzed to extract brain dynamics in terms of TFs between different cortical regions.

Before applying our method of blind identification of TFs, MEG time series data were temporally decorrelated by using a blind signal separation (BSS) method [Murata, 2001] [Kishida, 2003A]. Two BSS components were selected from their stochastic structure of periodic AEF in the similar manner as mentioned in [Kishida, 2003B]. The remixing matrix was applied to the two selected components to retrieve AEF MEG signals. To investigate inter-cortical dynamics of auditory brain functions, TFs between two positions as shown in Fig. 1 were calculated from the viewpoint of statistical inverse problem as mentioned in [Kishida, 1997] [Kishida, 2003A]. TFs of AEF were calculated to infer neural dynamics underlying the auditory brain responses. Their impulse functions were also evaluated.

METHODS

1 kHz pure tone bursts with the sound intensity of 80 dB SPL, which were made by Model SMP-4100 (Nihon-Koden Co.) and repeated once every 2.194 seconds (0.4556Hz), were delivered to the right ear of a healthy subject through a plastic tube of 1 m in length. MEG signals generated by 130 auditory trials were sampled at 700 Hz. MEG signals related to AEF can be extracted by using the temporal decorrelation method of BSS. In this method, two BSS components were selected in reference to periodical peaks of autocorrelation functions and power spectral density functions, since the periodic nature of the auditory stimuli used in this study can be utilized to characterize the MEG components evoked by them. That is, MEG time series, which were generated by the auditory stimuli presented in the frequency of 0.4556Hz, were temporally decorrelated to form two BSS components with peaks at 0.4556Hz and its higher harmonics in power spectrum density, before applying our blind identification of the TFs.

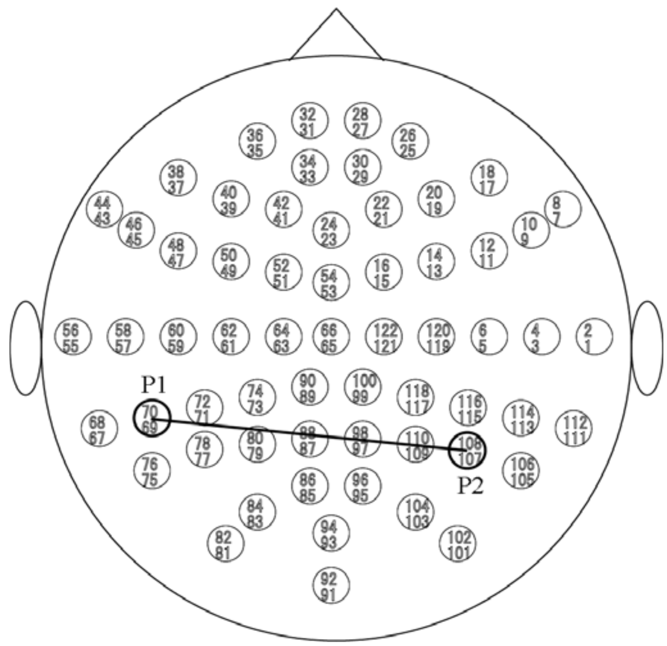

Figure 1. Location of MEG SQUID sensors, and odd or even number channel indicates $\frac{\partial B_r}{\partial x}$ or $\frac{\partial B_r}{\partial y}$ sensor.

Since MEG time series data were measured by 61 pairs of planar gradiometers of Neuromag122™ system; each pair measures the two independent tangential derivatives of the magnetic field component normal to the helmet-shaped surface approximating the shape of the scalp, the principal component for each sensor pairs was calculated, which approximately represents the intensity of the cortical activity just below the sensor location. We selected measurement variable $y_1(n)$ for the principal component of two dimensional data (69ch 70ch) at the position **P1** in Fig. 1, and also $y_2(n)$ for that of (107ch 108ch) at **P2**. The TFs between these two positions are calculated from the viewpoint of statistical inverse problem. Let two variables $y_1(n)$ and $y_2(n)$ be described by a following feedback system model with TFs $F^b_{12}(z^{-1})$ from **P2** to **P1** and $F^b_{21}(z^{-1})$ from **P1** to **P2**;

$$y_1(n) = F^b_{12}(z^{-1})y_2(n) + F^b_1(z^{-1})f_1(n)$$

$$y_2(n) = F^b_{21}(z^{-1})y_1(n) + F^b_2(z^{-1})f_2(n)$$

where z^{-1} is the backward time shift operator and n is discrete time.

In the case of positions **P1** and **P2**, a minimum phase innovation model of two varibales $y_1(n)$ and $y_2(n)$ was identified from principal components of AEF MEG time series data by the following steps:

1) calculation of correlation functions from two principal components,
2) sigular value decomposition of Hankel matrix of which elements were arranged by correlation function matrices,
3) selection of a stable solution of matrix Riccati equation,
4) determination of coefficient matrices A, B and A of innovation model as mentioned in Appendix A of [Kishida, 2003A].

Then, a closed loop TF matrix, $G(z^{-1})=C(I-Az^{-1})^{-1}B$, was obtained from the minimum phase innovation model of two variables $y_1(n)$ and $y_2(n)$, which can be rewritten into the representation of feedback system structure:

$$y_1(n) = F_{12}(z^{-1})y_2(n) + F_1(z^{-1})\gamma_1(n)$$
$$y_2(n) = F_{21}(z^{-1})y_1(n) + F_2(z^{-1})\gamma_2(n)$$

where $\gamma(n)$ is the innovation. Finally, TFs $F_{12}(z^{-1})$ and $F_{21}(z^{-1})$ were calculated from the closed loop TF matrix by our blind identification of TFs based on feedback system theory under the identifiable condition of feedback structure [Kishida, 1996]. After a model reduction [Kishida, 1997], TFs were determined by

$$F_{12}(z^{-1}):=G_{12}(z^{-1})/G_{22}(z^{-1}) \text{ and } F_{21}(z^{-1}):=G_{21}(z^{-1})/G_{11}(z^{-1}).$$

RESULTS

Averaged MEG signals showed clear N1 peaks at around 100 ms in latency (cf. Fig. 4, solid lines). The bode diagrams of identified TFs $F_{12}(z^{-1})$ and $F_{21}(z^{-1})$ between the positions **P1** and **P2** were shown in Fig. 2 by blue solid and red broken lines, respectively.

In this figure, bode diagrams, which were derived from seven innovation models with different number of singular values of Hankel matrix, were overlaid. The estimation of the TFs was robust regardless of identified innovation models of different sizes, which indicates the reliability of the results obtained by using the proposed method. Though this method can be applied to any pair of MEG channels as long as the minimum phase condition is held, the positions of P1 and P2 were selected as representative, since their TFs had robustness on shapes in changes of number of singular values from 10 to 16.

Their impulse response functions of seven identified TFs are shown in Fig. 3. Seven impulse responses from left hemisphere (**P1**) to right hemisphere (**P2**) were overwritten, and had constant negative values. Those of inverse direction had oscillations in positive and negative values. However, all changes of impulse responses decay within about 40 ms, and that their directional differences can be found from Fig. 3.

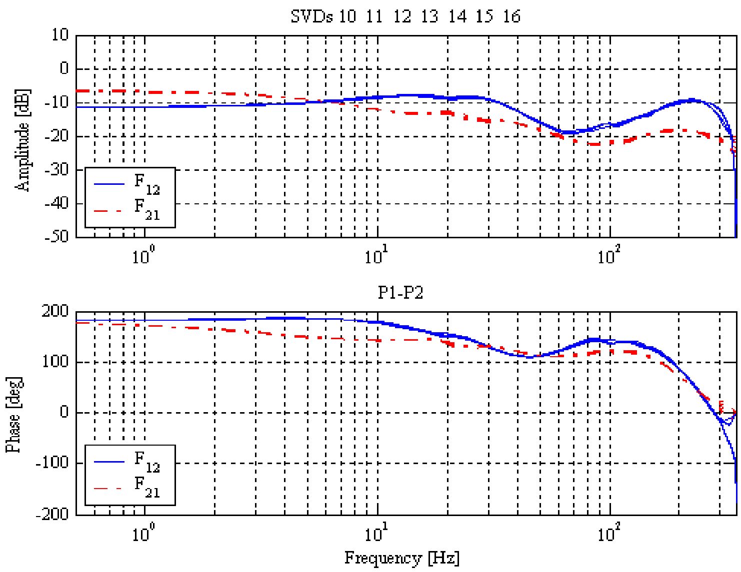

Figure 2. Bode diagrams of transfer functions between P1 and P2.

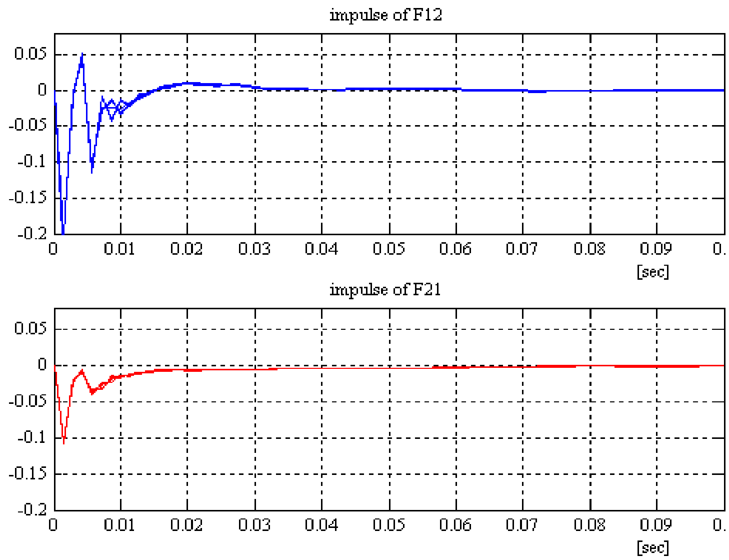

Figure 3. Impulse response functions of F_{12} and F_{21}

DISCUSSION

We proposed a new approach to investigate brain dynamics in terms of the TFs between cortical regions, and applied the technique to estimate TFs between a specific pair of MEG channels measuring auditory evoked brain responses. This method can be applied to any pair of MEG channels as long as the minimum phase condition is held.

In this study, we calculated the TFs between MEG data measured at two sensor locations instead of those in the source space, since dynamic property in the MEG sensor space when using planer gradiometer system is expected to represent the cortical activity just below the sensor location. If two positions are close to each other, transformation of the sensor space signal into source space activity by using an appropriate inverse procedure will be required to dissociate the neural activity in one location from another.

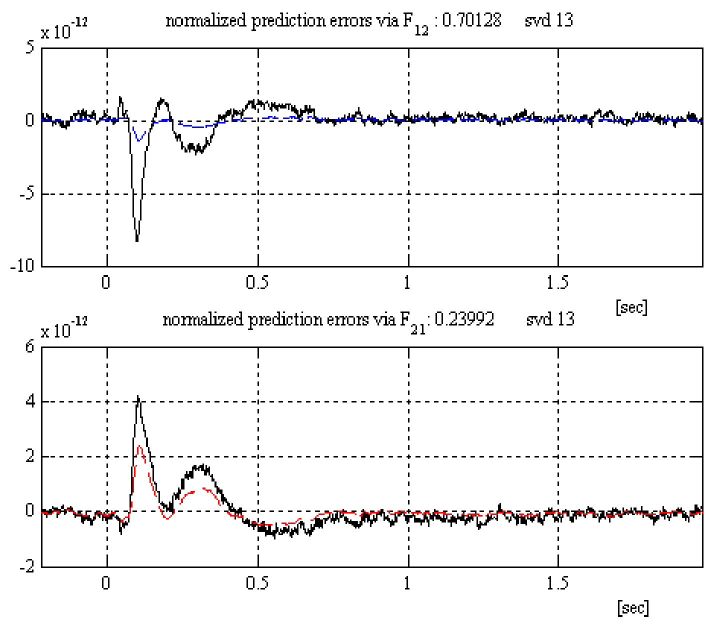

Figure 4. Comparison averaged waveform and predicted waveform using the identified model. The stimulus tone burst was presented at time 0.

Finally, let us compare the AEF MEG averaged waveforms with ones predicted by using identified innovation model of order 13 in order to check goodness of identified TFs. The solid line in the upper part of Fig. 4 is an averaged waveform av(y_1) of the principal component y_1 at **P1**. The blue broken line is a predicted waveform given by $F_{12}(z^{-1})av(y_2)$. The prediction error is defined by $\delta y_1 := av(y_1) - F_{12}(z^{-1})\, av(y_2)$. The best estimation of $F_{12}(z^{-1})av(y_2)$ is to predict $av(y_1)$, and then δy_1 is almost zero in the best case.

The normalized error value of $(\delta y_1/av(y_1))^2$ was calculated as 0.70128. In the lower part of Fig. 4 the red broken line is $F_{21}(z^{-1})av(y_1)$. The normalized error value of $\delta y_2 := av(y_2) - F_{21}(z^{-1})av(y_1)$ was 0.23992. Hence, it is concluded that the identification of $F_{21}(z^{-1})$ is better than that of $F_{12}(z^{-1})$.

From the above mentioned results we could propose our new dynamical approach in AEF to examine dynamics between SQUID channels. Although averaged waveforms used in the conventional MEG analysis are the first moment in terms of statistics, there remain much more dynamic properties included in MEG time series data. The present results suggest that brain dynamics can be extracted from correlation functions of the second moment.

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