Reduction of noise from magnetoencephalography data

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Abstract—*A noise reduction method for magnetoencephalography (MEG) data is proposed. The method is a combination of Kalman filtering and factor analysis. A state-space model for a Kalman filter was constructed using the forward problem in MEG measurement. Factor analysis provide estimations of noise covariances required by the Kalman filter to eliminate independent additive sensor noise. The proposed method supports independent component analysis (ICA), which is difficult to use in MEG analysis owing to the sensor noise. Numerical experiments were conducted to investigate the performance of the proposed method. In a single dipole case where the maximum signal-to-noise ratio (SNR) was − 10 dB, approximately equivalent to raw MEG data, noise-free signals were successfully estimated from noisy data; a 0.02 s delay of the peak latency and 15–40% of attenuation of the peak amplitude were observed. Moreover, in a multiple dipole case, independent components preprocessed with the proposed method had high correlation, 0.88 at the lowest, with correlation of 0.69 and 0.52 for those preprocessed with conventional bandpass filters. The results show that the noise reduction method reduces sensor noise effectively. High SNR-independent components are obtained by the proposed method. Real MEG data analysis was also demonstrated. The proposed method extracted auditory evoked responses from unaveraged single-trial data.*

Keywords—*Kalman filter, Factor analysis, Independent component analysis, Magnetoencephalography*

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1 Introduction

MAGNETOENCEPHALOGRAPHY (MEG) has recently attracted attention as a technique for researching human brain functions. MEG is the method used to measure the magnetic field generated by electrical neural activity. SQUID gradiometers are employed to detect a tiny magnetic field outside a skull non-invasively. The high temporal and spatial resolution are the main advantages of MEG, compared with other imaging methods, for example, f-MRI, PET and NIRS. Thus MEG can catch rapid cortical activity (HÄMÄLÄINEN *et al.*, 1993; BAILLET *et al.*, 2001).

MEG has already contributed to new knowledge about human brain functions and it is expected to play an increasingly important role in clinical treatments of, and investigations into, the human brain.

However, the issue of the low signal-to-noise ratio (SNR) in MEG measurement must first be addressed. The signals due to brain activity are very weak, typically in the order of 50–500 fT. Several kinds of noise and artifact, due to eye movements, blinking, heartbeats, electric power supply, earth magnetism etc, influence the desired signal, e.g. event-related responses. Bandpass filtering and stimulus-locked averaging across many trials are usually required to reduce sensor noise and spontaneous brain noise. Although these are powerful ways to improve the SNR, the imposition of many trials for averaging is a considerable burden for patients or experimental subjects. In addition, important temporal information can be lost.

It must also be considered that the inverse problem in MEG measurement entails difficulty because it is poorly posed and underdetermined. Noise always aggravates the difficulty. Biological artifacts and sensor-specific noise interfere with the estimation of the locations from which desired signals originate, and unwanted brain activities complicate the interpretations of the inverse solutions from MEG data. Noise and artifacts cause trouble during all phases of MEG analysis.

To resolve the issue, independent component analysis (ICA) for MEG analysis has been studied in recent years (VIGÁRIO *et al.*, 1997, 2000; IKEDA and TOYAMA, 2000; CAO *et al.*, 2000, 2002). ICA is one of the blind signal processing methods. It separates linearly mixed signals by the assumption of statistical independence of the signals. Several kinds of algorithm have been proposed. If the artifacts and brain signals are independent of each other, they can be separated by ICA.

Although ICA may be able to extract the signals from the data, including noise and artifacts, it does not function correctly under additive independent sensor noise, especially in MEG data analysis. ICA consists of two steps, preprocessing and a main algorithm to estimate independent components. The preprocessing with principal component analysis (PCA)

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produces orthogonalised signals before the main algorithm is performed, thereby reducing the calculation cost of the main algorithm.

In the preprocessing step, we are required to decide the number of independent components. A large amount of sensor noise makes this decision difficult. Another important issue is that the orthogonalisation of signals, excluding high-level sensor noise, and the subsequent estimation of independent components are crucial in practical MEG analysis. It has been proposed that factor analysis be substituted for PCA in the preprocessing (IKEDA and TOYAMA, 2000; CAO *et al.*, 2000). The orthogonalisation of signals may be successful with factor analysis. However, the influence of noise still seems to be a serious factor in MEG measurement. Factor analysis does not reduce the sensor noise sufficiently. Thus estimated independent components have low SNRs; furthermore, the desired components often cannot be obtained. An effective noise reduction method for taking advantage of ICA in MEG analysis and of the MEG data itself is thus needed.

In this paper, to alleviate the above-described problems in MEG measurement and analysis with ICA, we propose a signal processing technique that reduces the sensor noise from MEG data. This method consists of a combination of factor analysis and Kalman filtering. A state–space model for the Kalman filter of our method is constructed using the forward problem in MEG measurement. Factor analysis is employed to estimate the system and observation noise covariance matrices. Then, the Kalman filter is used to reduce sensor noise before the ICA procedure is performed.

The reliability of the solutions of some estimation problems, e.g. the inverse problems in MEG measurement, generally depend on prior information and assumptions. In cases where we cannot utilise reliable prior information, such as cases of neurophysiological research in progress, those should be minimised and simplified to obtain fair solutions. Our method is constructed of simple, minimum assumptions that preserve its reliability and usability: The forward solution of MEG is a linear system formula and suits a Kalman filtering problem. Thus the state–space equations are naturally described with mild assumptions. The Kalman filter does not need specific probability distributions to be identified of noise. Although the estimations of noise covariance required by the Kalman filter are always controversial, our method provides them by well-known factor analysis, and the result of the factor analysis is utilised, while the difficulty related to the inverse problem in MEG is avoided, namely the direct estimation of the system noise that we assume the current densities in a brain are driven by.

We conducted some numerical experiments and a real MEG analysis to confirm the effectiveness of our method. It was shown that the proposed noise reduction method with factor analysis and Kalman filtering eliminated sensor noise powerfully and supported ICA as a preprocessing technique.

2 Methods

2.1 *Forward problem in MEG measurement*

Biological electromagnetism, such as the neural electrical activity in a brain, is described by quasi-static approximation of the Maxwell equations, because the frequency spectrum of electrophysiological phenomena is below 1 kHz, and the time-derivative terms can be ignored. Therefore the magnetic field $\boldsymbol{B}(\boldsymbol{r})$ generated by brain activity is obtained from the Bio–Savart law (HÄMÄLÄINEN *et al.*, 1993; BAILLET *et al.*, 2001)

$$\boldsymbol{B}(\boldsymbol{r}) = \frac{\mu_0}{4\pi}\int \frac{\boldsymbol{J}(\boldsymbol{r}') \times (\boldsymbol{r} - \boldsymbol{r}')}{\|\boldsymbol{r} - \boldsymbol{r}'\|^3} d\boldsymbol{r}' \tag{1}$$

where $\boldsymbol{J}(\boldsymbol{r}')$ is the current density at $\boldsymbol{r}'$, and μ_0 is the permeability of tissue in a head equal to that of free space. Current density comprises two components, the primary and volume currents. The volume current is a result of the macroscopic electric field on charge carriers in the conducting medium. The primary current is considered to be neural activity. Equation (1) is transformed into an equation that has the terms of the primary and volume currents. The term of the volume current becomes a sum of surface integrals over boundaries of the conductors with different conductivities and depends on the differences between them. Thus, in an infinite homogeneous conductor, the volume current does not produce a magnetic field. A radial component of the primary current in a spherically symmetrical conductor does not contribute to the magnetic field (SARVAS, 1987; MOSHER *et al.*, 1999).

The magnetic field is linearly related to current dipoles. When we assume a discretised conductor for MEG analysis, the measurement $\boldsymbol{m}$ of MEG sensors can be written in a vector–matrix formula as the following linear system:

$$\boldsymbol{m} = L\boldsymbol{q} + \boldsymbol{\varepsilon} \tag{2}$$

where $\boldsymbol{q}$ represents the moments of all dipoles in the conductor, L represents the lead field matrix that expresses the sensitivities of the sensors, and $\boldsymbol{\varepsilon}$ represents the observation noise.

2.2 *Sensor noise reduction with a Kalman filter*

Kalman filtering is applied to several kinds of problem (TARVAINEN *et al.*, 2004; BELIGIANNIS *et al.*, 2004). Estimation problems to which a Kalman filter is applied can be classified into three types: prediction, filtering and smoothing problems. Here, we apply a Kalman filter to eliminate the noise, which is specific for each sensor, from MEG signals. This procedure supports successive ICA to reduce artifacts.

Kalman filtering is used to estimate the sequence of states of the dynamic system described as a state–space model (KALMAN, 1960; KALMAN and BUCY, 1961).

Let us assume that the moments of dipoles $\boldsymbol{q}(t)$ are driven by system noise $\boldsymbol{v}(t)$

$$\boldsymbol{q}(t+1) = \boldsymbol{q}(t) + \boldsymbol{v}(t) \tag{3}$$

where the first and second moments of $\boldsymbol{v}(t)$ are $E\{\boldsymbol{v}(t)\} = \boldsymbol{0}$ and $E\{\boldsymbol{v}(t)\boldsymbol{v}(l)^T\} = V(t)\delta_{tl}$. From the above assumption and the forward equation of MEG measurement (2) MEG data without observation noise, which can include artifacts, are described as follows:

$$\begin{aligned} \boldsymbol{x}(t+1) &= L\boldsymbol{q}(t+1) \\ &= L\boldsymbol{q}(t) + L\boldsymbol{v}(t) \\ &= \boldsymbol{x}(t) + L\boldsymbol{v}(t) \end{aligned} \tag{4}$$

In this study, it is assumed that the observation is constructed of MEG signals $\boldsymbol{x}(t)$, including desired signals and artifacts, e.g. unwanted brain activity, and 'sensor (observation) noise' $\boldsymbol{\varepsilon}(t)$, which is independently added to the signal of each sensor.

Then, observed MEG data with sensor noise are given as

$$\boldsymbol{m}(t) = \boldsymbol{x}(t) + \boldsymbol{\varepsilon}(t) \tag{5}$$

where $\boldsymbol{\varepsilon}(t)$ is the sensor noise the first and second moments which are $E\{\boldsymbol{\varepsilon}(t)\} = \boldsymbol{0}$ and $E\{\boldsymbol{\varepsilon}(t)\boldsymbol{\varepsilon}(l)^T\} = W(t)\delta_{tl}$. Therefore we set the state–space model for the Kalman filter to be as follows:

$$\boldsymbol{x}(t+1) = \boldsymbol{x}(t) + L\boldsymbol{v}(t) \tag{6}$$

$$\boldsymbol{m}(t) = \boldsymbol{x}(t) + \boldsymbol{\varepsilon}(t) \tag{7}$$

where L is the lead field matrix.

Furthermore, we assume that an initial state x_0 is uncorrelated to the system and observation noises, $E\{x_0\} = \bar{x}_0$ and $V\{x_0\} = X_0$. Under the prescribed assumptions, the estimation of the state sequence, namely the sensor noise-free MEG signals, is obtained by the recursive prediction and correction included in the following algorithm:

$$\hat{x}(t) = \tilde{x}(t) + K(t)\,(m(t) - \tilde{x}(t)) \tag{8}$$

$$K(t) = M(t)\,(M(t) + W(t))^{-1} \tag{9}$$

$$P(t) = M(t) - K(t)M(t) \tag{10}$$

$$\tilde{x}(t+1) = \hat{x}(t) \tag{11}$$

$$M(t+1) = P(t) + LV(t)L^T \tag{12}$$

In particular, when $V(t)$ and $W(t)$ are time-invariant in a state–space model that is observable and controllable, $P(t)$ converges to a constant value. Then, a stationary Kalman filter is obtained

$$\hat{x}(t) = (I - K)\hat{x}(t-1) + Km(t) \tag{13}$$

$$K = PW^{-1} \tag{14}$$

where I is the identity matrix. P satisfies the following equation:

$$P = [(P + LVL^T)^{-1} + W^{-1}]^{-1} \tag{15}$$

In this study, the system and observation noises are assumed to be stationary during the MEG measurement. We adopt a stationary Kalman filter algorithm in (13) and (14).

Kalman filtering requires knowledge of the system noise covariance matrix V and observation noise covariance matrix W. Factor analysis is utilised to estimate the noise covariances in the following Section.

2.3 *Estimation of noise covariances with factor analysis prior to Kalman filtering*

Factor analysis (FA) is one of the methods for multivariate data analysis and is utilised in the preprocessing of ICA (IKEDA and TOYAMA, 2000; CAO *et al.*, 2000).

In FA, factor loading matrix Λ and sensor noise covariance (covariance of unique factors) matrix W are estimated. The observation $m(t)$ is modelled as follows:

$$m(t) = \Lambda f(t) + \varepsilon(t) \tag{16}$$

$$f(t) = [f_1(t), f_2(t), \ldots, f_n(t)]^T$$

$$E\{f_i(t)\} = 0,\ E\{f_i(t)\, f_j(t)\} = \delta_{ij}$$

where f_i and ε_i are called the common factor and unique factor. From (5) and (16), we can determine that $x(t) = Lq(t) = \Lambda f(t)$.

There are several methods to conduct FA, e.g. the unweighted least squares method, principal factors method and maximum likelihood method (IKEDA and TOYAMA, 2000; CAO *et al.*, 2000). In this study, we adopt the unweighted least squares method, which can be used easily owing to the simplicity of the formulation and the algorithm. Besides, it requires fewer prior conditions or assumptions, e.g. a probability distribution function, than the others. However, any methods for FA can be applied to estimate the noise covariances.

The estimation is achieved by solving the following problem:

$$\min_{\Lambda, W} \mathrm{tr}\{(S - \Lambda\Lambda^T) - W\}^2 \tag{17}$$

where S is an observed covariance matrix.

To minimise the cost function, the algorithm is derived as

$$\Lambda_{t+1} = \Lambda_t + \eta(S - \Sigma_t)\Lambda_t \tag{18}$$

$$W_{t+1} = \mathrm{diag}(S - \Lambda_{t+1}\Lambda_{t+1}^T) \tag{49}$$

$$\Sigma_{t+1} = \Lambda_{t+1}\Lambda_{t+1}^T + W_{t+1} \tag{20}$$

We can use the sensor noise covariance W estimated by FA for the Kalman filter algorithm. On the other hand, it is impossible to estimate V directly, but LVL^T in (15) can be estimated from the result of FA, as follows.

$\Lambda\Lambda^T$ is the covariance of $x(t)$. When the sample number of MEG data τ is sufficiently large, the following relationship holds, as $E\{v(k)v(l)^T\} = 0$, $(k \neq l)$, and state equation (6) holds:

$$\begin{aligned}\Lambda\Lambda^T &= \frac{1}{\tau}\left\{\sum_{t=1}^{\tau} x(t)x(t)^T\right\} \simeq \frac{1}{\tau}L\{\tau v(1)v(1)^T \\ &\quad + (\tau-1)v(2)v(2)^T + (\tau-2)v(3)v(3)^T \\ &\quad + \cdots + v(\tau)v(\tau)^T\}L^T \\ &= \frac{1}{\tau}L\left\{\sum_{t=1}^{\tau}(\tau+1-t)v(t)v(t)^T\right\}L^T\end{aligned} \tag{21}$$

Normalising the factor inside the braces $\{\cdot\}$ on the right-hand side of (21) by $\sum_{t=1}^{N} t = (1+\tau)\tau/2$, we obtain the weighted average of $v(t)v(t)^T$. Thus the estimation of LVL^T required for Kalman filtering is obtained by the following normalisation of $\Lambda\Lambda^T$ estimated with FA:

$$\frac{2}{\tau+1}\Lambda\Lambda^T \simeq LVL^T \tag{22}$$

With this estimation, we can avoid the difficulty in estimating V directly; it includes some issues related to the inverse problem in MEG measurement.

2.4 *Independent component analysis following sensor noise reduction*

Independent component analysis (ICA) is a method for extracting independent components based only on observation (HYVÄRINEN *et al.*, 2001). The observation data are modelled as a mixture of unknown sources. If artifacts and desired signals are independent, we can separate the artifacts from the signals through ICA (VIGÁRIO *et al.*, 1997, 2000; IKEDA and TOYAMA, 2000; CAO *et al.*, 2000, 2002).

Preprocessing with principal component analysis (PCA) is usually conducted to reduce the dimension and to make the signals uncorrelated. After noise reduction by the combination of FA and Kalman filtering, we apply the following procedure for the PCA:

$$y(t) = (\Lambda^T\Lambda)^{-1}\Lambda^T\hat{x}(t) \tag{23}$$

Then, ICA estimates independent components under the assumption that the signals are described as follows:

$$y(t) = Hs(t) \tag{24}$$

where $\boldsymbol{y}(t)$ is interpreted as the mixed data that, by an unknown matrix H, mix unknown independent components $\boldsymbol{s}(t)$.

The goal of ICA is to estimate an unmixing matrix U that is a generalised inverse of H, so that the estimated independent components $\hat{s}(t)$ can be obtained as

$$\hat{s}(t) = U\boldsymbol{y}(t) \tag{25}$$

Several algorithms have been shown to be effective for estimating U. We adopt the FastICA algorithm based on a fixed-point method (HYVÄRINEN *et al.*, 2001; CAO *et al.*, 2002), because it has the advantages of fast convergence, lack of a learning rate etc. This algorithm extracts independent components one by one using the row vector $\boldsymbol{u}^T$ of U calculated by the following algorithm:

$$\tilde{\boldsymbol{u}}_t = \boldsymbol{u}_t - \frac{E[yg(\boldsymbol{u}_t^T y)] - \beta \boldsymbol{u}_t}{E[g'(\boldsymbol{u}_t^T y)] - \beta} \tag{26}$$

$$\boldsymbol{u}_{t+1} = \frac{\tilde{\boldsymbol{u}}_t}{\|\tilde{\boldsymbol{u}}_t\|} \tag{27}$$

where $g(z) = z^3$ or $g(z) = \tan h(z)$.

3 Numerical studies

Numerical experiments were carried out to investigate the performance of our proposed method. The results of the noise reduction with the FA and Kalman filter combination (FA-processed Kalman filter) and of ICA following the noise reduction were compared to those with bandpass filtering, which is the usual noise reduction method used in MEG data processing.

In each experiment, MEG data were simulated by the forward equation of MEG measurement. Gaussian noises were added to the simulated MEG data as sensor noises. The conductor was assumed to be a homogeneous hemispherical object with radius of 8 cm, which was discretised to 1152 grid points at 1 cm intervals.

3.1 *Numerical experiment 1*

In the first experiment, a single dipole on $(x, y, z) = (0, 4, 0)$ was placed in the conductor to simulate brain activity in a lateral lobe, e.g. an auditory evoked response. The SNRs of the sensors are shown in Fig. 1. Below, we examine and discuss the effectiveness of the proposed method and the robustness to errors in the number of common factors of the simulation. The sampling rate was 1024 Hz. Noise reduction by an ideal low-pass filter whose cutoff was at 40 Hz (40 Hz LPF) was implemented as a reference.

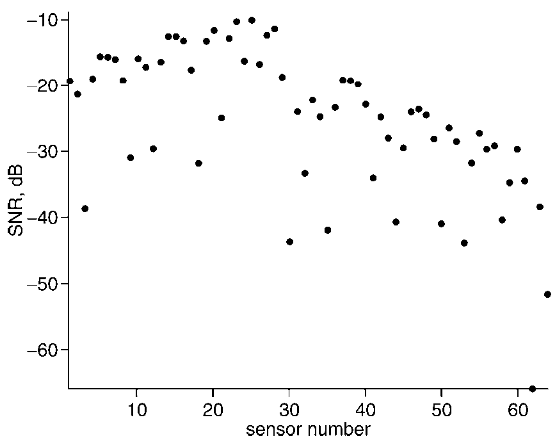

Fig. 1 *SNR of each sensor in single dipole case*

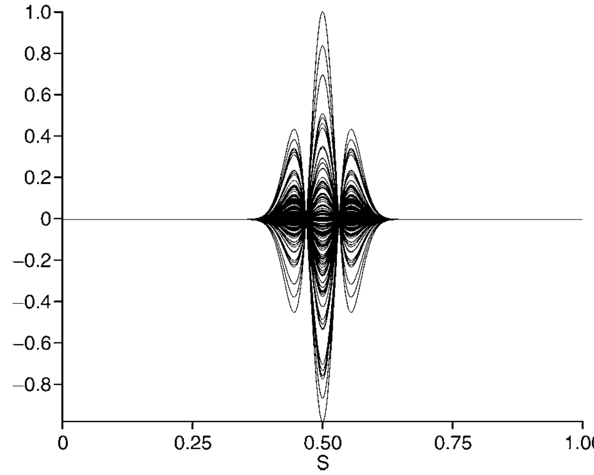

Fig. 2 *64 noise-free MEG signals in the first numerical experiment*

3.2 *Result 1*

Our proposed method reduced the sensor noise significantly. Figs 2 and 3 show the 64 superimposed original noise-free signals and MEG signals obtained by the FA-processed Kalman filter, respectively. They are normalised by the maximum value of the original signals. An approximate time delay of 0.02 s and attenuation of the amplitude occurred with the proposed method. The amplitudes of the estimated signals at their peaks are about 60–85% of the original ones. However, the FA-processed Kalman filter was able to extract the features of the original noise-free MEG data despite this noisy situation. On the other hand, a considerable amount of noise still remained in the MEG data processed with 40 Hz LPF, as shown in Fig. 4.

The proposed method succeeded in the noise reduction, even when the number of common factors was incorrect. Fig. 5 shows the eigenvalues of the covariance matrix of the MEG data after the noise reduction by the FA-processed Kalman filter with one common factor, that is, with the correct number of common factors, and Fig. 6 shows the eigenvalues of the covariance matrix of the data processed by our method with five common factors. Even though the number of common factors was set wrongly as five, the maximum eigenvalue contributed 85.9% of the total value. This indicated that the sensor noises and the redundant factors were eliminated effectively.

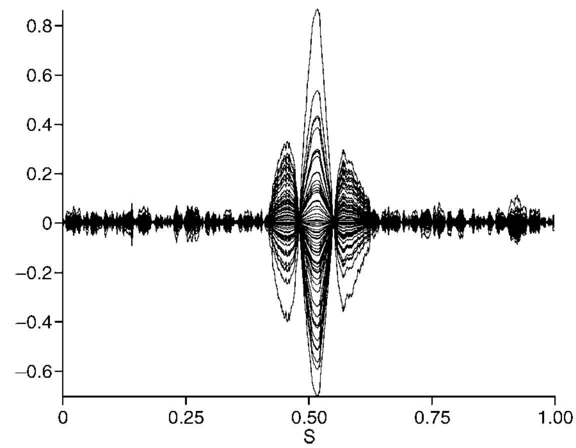

Fig. 3 *MEG signals processed with FA and Kalman filtering in first numerical experiment*

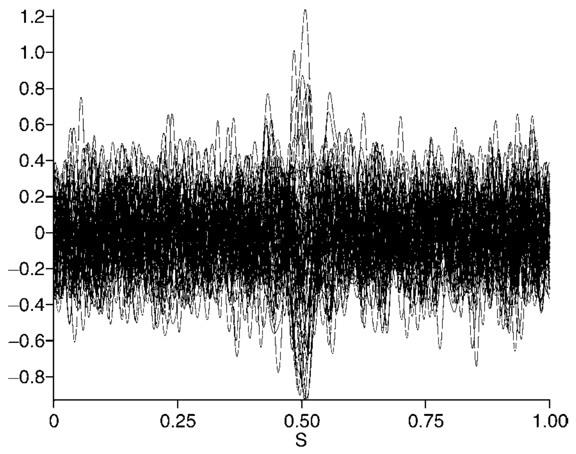

Fig. 4 *MEG signals processed with a 40 Hz low-pass filter in first numerical experiment*

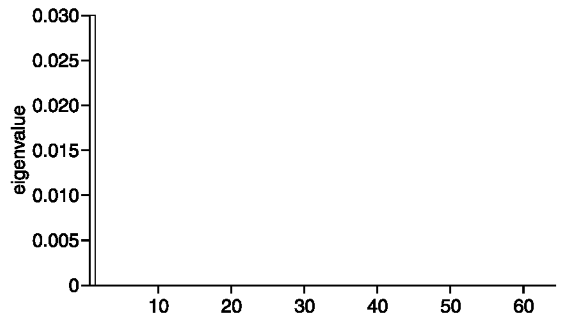

Fig. 5 *Eigenvalues of the covariance matrix of the FA and Kalman-filtered MEG data with one common factor in first numerical experiment*

3.3 *Numerical experiment 2*

We also demonstrated the noise reduction in a case of multiple independent components (ICs) in a second numerical experiment to investigate the influence of the FA-processed Kalman filtering as a method for preprocessing ICA. Sources were located at $(x, y, z) = (0, 4, 0)$, $(0, -3, 0)$, $(0, 0, 5)$ and $(-7, 0, 3)$. Fig. 7 shows the time series of each source activity. The SNR of each sensor is shown in Fig. 8.

The sampling rate was 512 Hz. Two kinds of filter, i.e. a 40 Hz low-pass filter (LPF) and an ideal bandpass filter (BPF) whose passband was from 1 to 100 Hz (1–100 Hz BPF) were compared with the filter used in our method. Both of these filters are conventionally used in MEG measurement. The number of common factors was given as four. The issue of the number of common factors was excluded to investigate the effect of the connection between the Kalman filter and ICA.

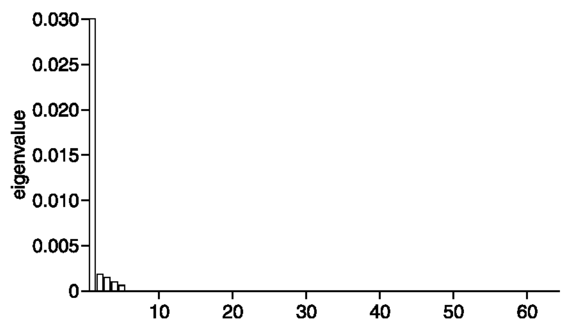

Fig. 6 *Eigenvalues of the covariance matrix of FA and Kalman-filtered MEG data with five common factors in first numerical experiment*

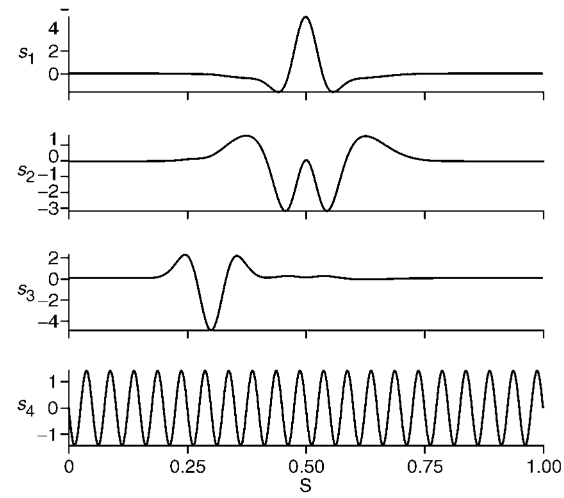

Fig. 7 *Source signals: the signals s_1–s_4 are located at $(x, y, z) = (0, 4, 0)$, $(0, -3, 0)$, $(0, 0, 5)$, and $(-7, 0, 3)$, respectively*

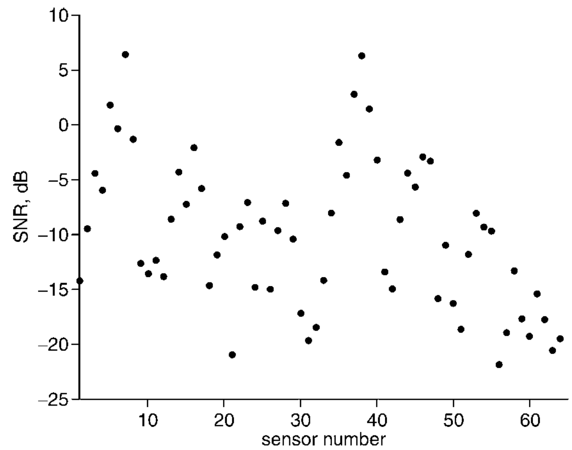

Fig. 8 *SNR of each sensor in the case of multiple ICs*

After each noise reduction, four ICs were estimated by the FastICA algorithm.

3.4 *Result 2*

We were able to obtain four ICs that agreed with the original source signals by ICA after each noise reduction. Figs 9–11

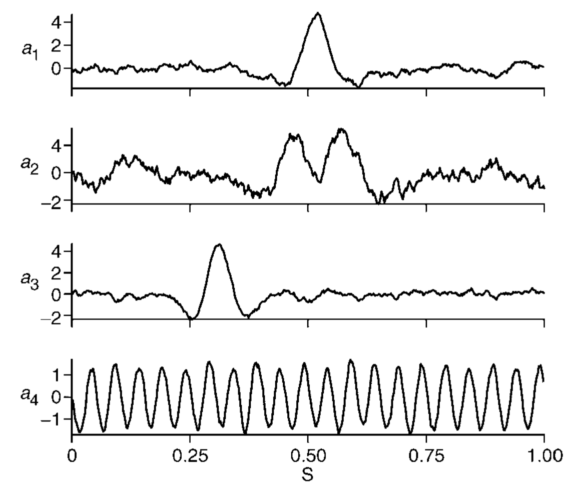

Fig. 9 *Independent components estimated from FA-processed, Kalman-filtered MEG data*

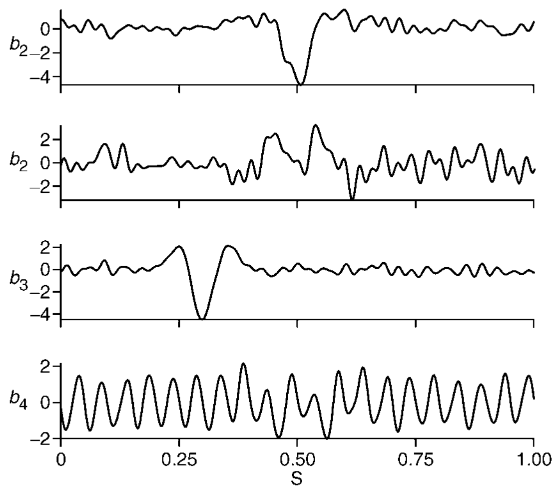

Fig. 10 *Independent components estimated from 40 Hz low-pass filtered MEG data*

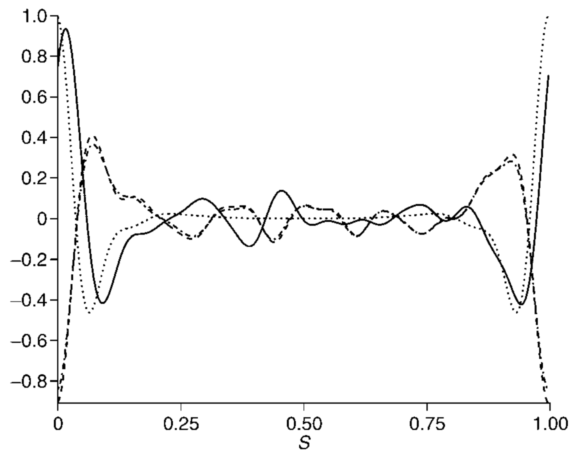

Fig. 12 *Cross-correlation functions between (——) s_1 and a_1, (– – –) s_1 and b_1, (–·–·–) s_1 and c_1. (······) autocorrelation of s_1*

Table 1 Maximum absolute values of cross-correlation functions

		a_i (proposed)	b_i (40 Hz LPF)	c_i (1–100 Hz BPF)
s_i	$i = 1$	0.938	0.909	0.844
	2	0.879	0.692	0.526
	3	0.968	0.954	0.919
	4	0.989	0.939	0.985

show the ICs estimated by the proposed method, the 40 Hz LPF method and the 1–100 Hz BPF method, respectively. The estimated ICs in Fig. 9 coincided well with the source signals. It was confirmed that the state-space model constructed with the forward equation of MEG measurement and the estimation of the system noise covariance were reasonable.

There were high correlations between the ICs estimated by the proposed noise reduction and ICA and the corresponding original signals. Fig. 12 shows the autocorrelation function of s_1 and the cross-correlation functions between s_1 and corresponding ICs a_1, b_1 and c_1. They were normalised by the maximum of the autocorrelation function. In addition, the maximum absolute values of the cross-correlation functions between the source signals and the corresponding estimated ICs are shown in Table 1.

3.5 *Discussion*

The proposed method was shown significantly to eliminate sensor noise. In the first numerical experiment, the maximum SNR of the simulated MEG data was -10 dB and agreed with that of typical evoked fields in the order of 10^2 fT, such as auditory and sensory evoked fields. This can be estimated from the fact that, in the case of the typical evoked field, we attained a 90% goodness-of-fit (GOF) in dipole fitting after averaging in the order of 10^2 trials. This estimation suggests that the FA-processed Kalman filter method can at least significantly reduce the number of trials required for averaging; in addition, the method can extract desired signals from unaveraged MEG data.

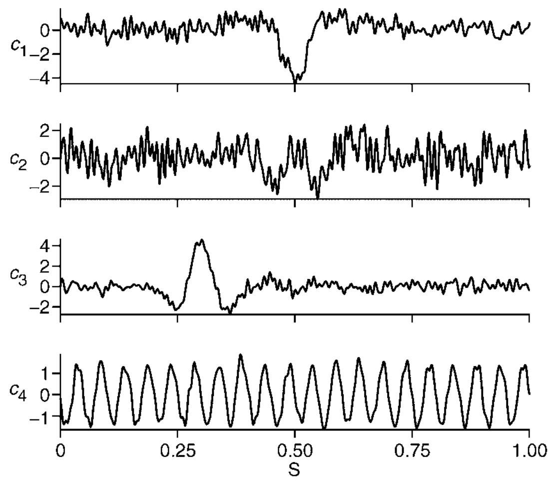

Fig. 11 *Independent components estimated from 1–100 Hz bandpass-filtered MEG data*

The FA-processed Kalman filter is robust to the error in the number of common factors to some extent. This constitutes an advantage of our method for the preprocessing of ICA.

The number of ICs must be decided before preprocessing; however, high-level noise makes this decision difficult. The number of ICs is usually determined by referral to the contribution ratios of PCs. In numerical experiment 2, although the true number of ICs was four, we needed nine PCs to achieve an 80% contribution in 40 Hz LPF data; 25 PCs were needed in 1–100 Hz BPF data. Some criteria, such as minimum description length (MDL) or Akaike's information criteria (AIC), have been shown to be useful for refining the number of ICs. However, to determine the actual number of ICs is impossible, especially in practical MEG analysis. Our method is also able to utilise those criteria in the FA step to estimate the number of common factors. Moreover, it does not tend to be influenced by an incorrect number of common factors, as shown in numerical experiment 1.

The proposed method overcomes the issue of the orthogonalisation of signals under independent additive noises and obtains high SNR ICs through sensor noise reduction with Kalman filtering. Sensor noise causes unsuccessful orthogonalisation of signals, with the eventual result that the desired ICs cannot be obtained. With its powerful noise reduction, our method allows extraction of ICs from low SNR data. In numerical experiment 2, the original signal s_2 in Fig. 7 was located at the position $(x, y, z) = (0, -3, 0)$, which was further from the sensor array than the other sources. Therefore it was weaker and had a lower SNR than the other sources. We were able to obtain IC a_2, the estimation of s_2, which showed high correlation with the original signal s_2. In addition, the FA-processed Kalman filter eliminated the sensor noise without any difficulty is choosing a frequency band.

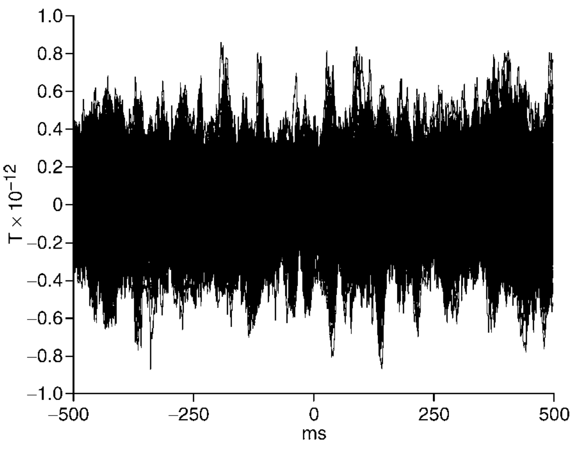

Fig. 13 *Single-trial AEF data*

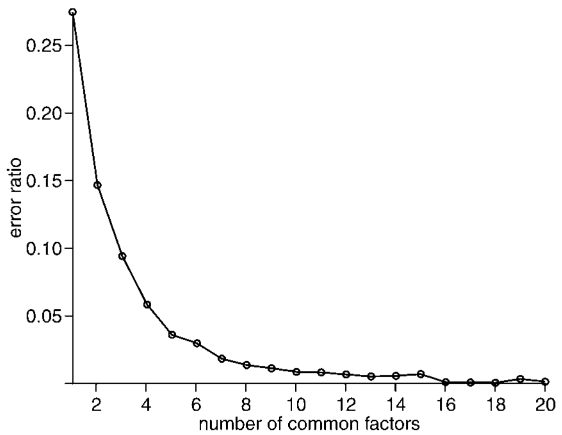

Fig. 14 *Error ratios between the estimated and observation covariances*

4 Real MEG data analysis

Finally, a real MEG data analysis with the FA-processed Kalman filter and ICA was demonstrated. Unaveraged single-trial data of auditory evoked fields (AEFs) were processed with the proposed method.

4.1 *Experimental conditions*

AEF data were acquired using 230 channel gradiometers of a whole-head MEG system*. The subject was a 27-year-old male. 1000 Hz tone bursts were presented to both ears simultaneously. The sampling rate was 1000 Hz, and a data set of the trial was 1000 ms long, 500 ms each for the pre- and post-stimulus terms. The data were filtered on-line to a bandwidth of 0.03–200 Hz. We performed noise reduction with the FA-processed Kalman filter for the single-trial data shown in Fig. 13.

4.2 *Results and discussion*

In the FA step, we decided the number of common factors by referring to the variation of the error between the estimated and observed covariance, namely (17). When the number of common factors was ten and above, the estimation errors were adequately minimised by less than 1%, and the variation converged, as shown in Fig. 14. This indicates that the model with ten common factors could explain the observation covariance sufficiently. We adopted the noise covariances estimated

*Yokogawa, Japan

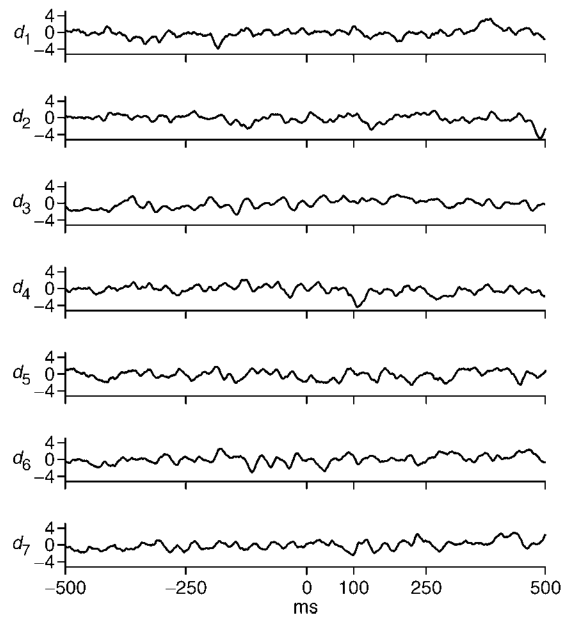

Fig. 15 *Independent components estimated from the single-trial AEF data*

with ten common factors. The FA-processed Kalman filtering was implemented with the estimated noise covariances.

In the ICA step, seven PCs contributed 94.2% to the total value in the Kalman-filtered data covariance, whereas 22 PCs were needed to achieve a 90.0% contribution in the raw data covariance. Therefore we estimated only seven ICs by FastICA. Fig. 15 shows the estimated ICs.

IC d_4 shown in Fig. 16 has its peak around 100 ms, and it can be interpreted as a typical N1m of AEF. Fig. 17 shows the isofield contour map of the magnetic field pattern of IC d_4, which suggests the existence of bilateral brain activity in the neighbourhood of the auditory cortexes.

In this real MEG data analysis, the proposed method extracted the AEF signal from the unaveraged, single-trial MEG data. The result shows that our method is robust to sensor noise in real MEG measurement and confirms the practical utility of our method. The robustness to the error in the number of common factors was also confirmed. By the Kalman filtering, the redundant factors were reduced sufficiently to be ignored, as with the case of the incorrect number of common factors in numerical experiment 1, and we succeeded in refining the number of components in the ICA step. Those results not only show the effectiveness of the FA-processed Kalman filter but also support the validity

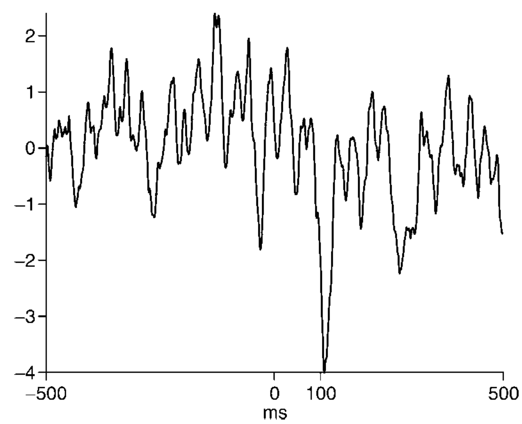

Fig. 16 *Independent component d_4*

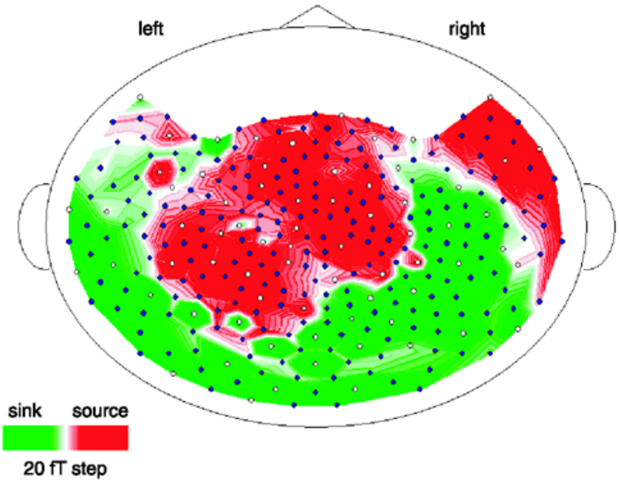

Fig. 17 *Isofield contour map of the magnetic field pattern of the extracted independent component d_4; red and green regions show positive and negative magnetic fields, respectively*

of our numerical studies. We assumed the sensor noise was Gaussian in the previous numerical experiments. However, even if sensor noise in real MEG data does not satisfy the assumption of Gaussianity, our method still retains its effectiveness, as the Kalman filter is the optimum linear minimum variance filter regardless of the Gaussianity of noise.

5 Conclusions

For MEG analysis, a noise reduction method that utilises a Kalman filter and factor analysis is proposed. In this method, a state-space model is constructed using the forward problem in MEG measurement. Factor analysis estimates the system and observation noise covariances for the Kalman filter. Kalman filtering reduces the sensor noise and estimates sensor noise-free MEG data. ICA follows the noise reduction to eliminate artifacts.

Even though the assumptions for the state-space model and the approximation of the noise covariances are very simple, the sensor noise in the MEG data was effectively reduced, in addition, our method supported ICA well in some numerical experiments. We could obtain high SNR-independent components whose source positions were farther from the sensor array and had lower SNR.

Our proposed method can reduce the number of trials for averaging and eliminate noise without the requirement of choosing a frequency band. It can also alleviate two problems in preprocessing, namely, the decision regarding the number of ICs and the orthogonalisation of signals under additive independent noise.

The noise reduction method, with the combination of factor analysis and Kalman filtering, alleviates the burden for patients and experimental subjects in MEG measurement; moreover, it relieves the problems in MEG analysis.

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