ICA Methods for MEG Imaging

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ABSTRACT

Activity of individual cortical sources cannot be uniquely imaged when MEG data is a sequence of complex spatial pattern of multiple cortical sources. Auxiliary constraints integrated into the imaging equations are required to remove the mathematical ambiguity. Therefore, it is important to adapt source separation techniques to MEG imaging. It is much easier to accurately image field patterns of isolated brain electric sources. Therefore, we demonstrate how a combination of second and fourth order ICA methods can be used to remove noise and isolate source activity for improved MEG imaging accuracy. A second order ICA technique was used to extract respiratory and eye movement artifact by exploiting cross-correlation differences over time between cortical sources and artifact. For brain electric source separation, a fourth order ICA technique that quantified probabilities of simultaneous source activity was used to separate brain electric sources characterized by bursts of oscillatory circuit activity.

INTRODUCTION

MEG data consists of an unknown mixture of noise, artifact and signals from unknown brain electric sources. Often these sources are compact cortical networks that are sequentially activated to perform simple or complex tasks. However, coherent activity across an extended region is often simultaneously present with compact source activation or as a primary mode, such as during sleep. Unfortunately, MEG recorded source activity is not unique to the true distribution of brain electric sources and contains significant artifact. It is usually necessary to eliminate artifact and desirable to extract the spatial-temporal MEG signal for each source prior to imaging source activity. Frequently, popular methods of removing noise, such as frequency filtering or signal averaging, are inadequate or inappropriate for removing artifact. However, much of this artifact is due to semi-stationary rhythms of respiration, slow eye movements and heart activity that can be separated from brain electric signals using a combination of second order (time correlation) and fourth order (activation probability) independent component analysis techniques. Finally, the time course of spontaneous and task related brain electric source activity is characterized by bursts of oscillatory activity of limited duration. In addition, sources are usually uncorrelated or sequentially activated with limited temporal overlap. This temporal behavior can be exploited by fourth order ICA techniques for isolating neuronal source activity and the corresponding spatial pattern representation in MEG array.

METHODS

MEG studies: Our 148 channel whole head Neuromagnetometer (WH2500 Magnes, 4D Neuroimaging), was used to measure magnetic fields in five individuals for one hour of quiet rest during which they fell asleep. While in a supine position in a quiet dark magnetically shielded room, each subject was instructed to remain awake during the first two minutes of the study. Simultaneous recording of ECG, EOG, and C3, C4, Oz EEG channels were stored with the MEG data. For each subject 10 seconds of MEG data for awake, transition to stage 1 sleep, and stage 1 sleep were selected for imaging cortical activation. These data contained significant artifact associated with respiration and heart activity. MEG data was sampled at 508 Hz and initially band-pass filterd 0.1-100 Hz before disk storage. During analysis, these data were further band-pass filtered 0.2 to 25 Hz. Heart artifact was removed using a fourth order ICA technique applied to the MEG data and utilized the simultaneously recorded ECG. Respiration artifact was eliminated using a second order time correlation ICA technique. Estimates of time dependent brain electric network signals and corresponding MEG spatial patterns were estimated using a fourth order probability technique.

ICA Methods: The second order technique used is AMUSE [1]. This technique is useful for separating sources based on changes in second order correlation that occur with time. Mathematically this relationship is:

With $\mathbf{B}$ and $\mathbf{B}_\tau$ are (channel by time = row by column) matrices of MEG data offset by time increment, τ.

$$\mathbf{B}_\tau = \boldsymbol{\alpha}(\tau)\mathbf{B} + \left[\mathbf{B}_\tau - \boldsymbol{\alpha}(\tau)\mathbf{B}\right] \quad \text{with } \boldsymbol{\alpha}(\tau) = \mathbf{B}_\tau\mathbf{B}[\mathbf{B}\mathbf{B}^T]^{-1} \quad \text{then:}$$

$$\mathbf{B}\mathbf{B}_\tau^T + \mathbf{B}_\tau\mathbf{B}^T = \mathbf{B}\mathbf{B}^T\boldsymbol{\alpha}(\tau)^T + \boldsymbol{\alpha}(\tau)\mathbf{B}_\tau\mathbf{B}^T \quad \text{with singular value decomposition: } \mathbf{B} = \mathbf{U}\boldsymbol{\lambda}\mathbf{V}^T \tag{1}$$

using the above relationships, the second order ICA components are:

$$\mathbf{V}_{\mathbf{ICA}} = \mathbf{V}\mathbf{U}_{\mathbf{ICA}} \quad \text{with } \mathbf{V}\mathbf{V}_\tau^T + \mathbf{V}_\tau\mathbf{V}^T = \mathbf{U}_{\mathbf{ICA}}\boldsymbol{\lambda}_{\mathbf{ICA}}\mathbf{V}_{\mathbf{ICA}}^T$$

The fourth order technique is implemented in two steps. First a singular value decomposition of the MEG data, $\mathbf{B}$, defined is performed to obtain the singular value time series components, $\mathbf{V} = [\mathbf{v}_1, \ldots, \mathbf{v}_N]$ defined in Equation 1. Noise reduction and elimination of noise components can be performed during this step. Second, the fourth order correlations $\mathbf{C}_{ijkl}$ of the vectors, $\mathbf{v}_i$, $\mathbf{v}_j$, $\mathbf{v}_k$, $\mathbf{v}_l$, are calculated for all combinations of i, j, k and l. These correlations can be used to calculate fourth order cumulants [2] related to component density distributions. However, for the orthonormal vectors, $\mathbf{V}$, the fourth order correlations can be utilized to obtain fourth order independent components. The goal of the technique used in this research is to rotate the singular value decomposition vectors, V, until fourth order correlations, $\mathbf{C}_{jjjk}$, and $\mathbf{C}_{jjkk}$ have been minimized. The ICA technique, JADE [2], has been developed for this purpose. However, we have developed a 4th order technique that diagonalizes a sequence of ICA component probability operators, $\mathbf{P}_\mathbf{P}(t)$, (subscript corresponds to the particular ICA component). ICA components are only estimates of the unknown brain electric sources, (See [1] for identifiability factors). Therefore, we utilize the squared amplitude of an ICA component, $\mathbf{v}_\mathbf{P}(t)^2$, at each instant in time as a measure of the probability that the corresponding unknown source, $\mathbf{s}_\mathbf{P}(t)$, is active. Thus, fourth order correlations $\mathbf{C}_{jjkk}$ can be interpreted as the average probability per time increment that sources $\mathbf{s}_j(t)$ and $\mathbf{s}_k(t)$ are simultaneously active at time points within the time interval, t_1 to t_2. The fourth order correlations $\mathbf{C}_{jjjk}$ address how the sources $\mathbf{s}_j(t)$ and $\mathbf{s}_k(t)$ constructively or destructively interfere when they are part of a combined component. Since fourth order separation techniques minimize these cross correlations, the ICA components tend to be active during short time intervals that do not overlap, Fig. 1.

In our technique, the probability operator for any ICA basis vector, $\mathbf{v_P}(t)$ is the diagonal matrix, $\mathrm{diag}(\mathbf{v_P}(t)^2)$, with all time components for the time interval, t_1 to t_2, on the diagonal. Next, a recursive algorithm is used to consturct ICA basis vectors, $\mathbf{V_{ICA}} = [\mathbf{v_1}, \ldots, \mathbf{v_P}, \ldots, \mathbf{v_N}]$, such that $\mathbf{v_P}$ is the principal eigen-vector $\mathbf{u_1}$ with eigen-value $\boldsymbol{\lambda}_1 = \mathbf{C}_{pppp}$ of the correlation operator $\mathbf{P_P} = \mathrm{diag}(\mathbf{v_P}(t)^2)$ in the vector subspace, $[\mathbf{v_P}, \ldots, \mathbf{v_N}]$.

$\mathbf{v}_{\mathrm{P}}$ is the principal eigen-vector of $\mathbf{V}_{\mathrm{P}} = \left[\mathbf{v}_{\mathrm{P}}, \cdots, \mathbf{v}_{\mathrm{N}}\right]$

where

$$\mathbf{V}_{\mathrm{P}}^{\mathrm{T}} \mathbf{P}_{\mathrm{P}} \mathbf{V}_{\mathrm{P}} = \boldsymbol{\lambda} = \text{eigen-value matrix} \qquad (2)$$

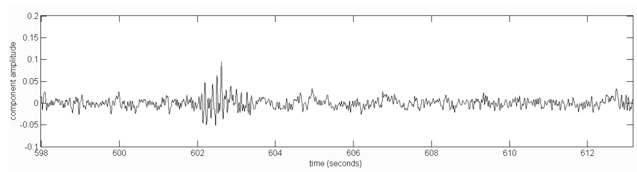

Fig. 1 A fourth order ICA component extracted from MEG data including the transition for awake to stage 1 sleep has the majority of component activity localized within a short time interval.

RESULTS

ECG heart artifact was eliminated from the MEG data by setting $\mathbf{P_P}(t)$ in equation 2 to the normalized squared amplitude of the simultaneously recorded ECG channel. The first ICA component of this 4^{th} order decomposition corresponds to the heart artifact in the MEG data, Fig 2. The second order AMUSE technique is more appropriate for extracting respiration and eye movement artifact which is continuous through the data, Fig. 3. For MEG imaging, twelve 4^{th} order ICA components corresponding to neuronal activity were extracted for each of the awake, transition, and stage 1 data segments. An ICA source component for one subject is shown in Fig. 1. For each ICA component, the MEG array spatial representation was imaged using MR-FOCUSS [3,4] and combined to obtain the sequence of activation for all cortical model locations. During sustained wakefulness, activity in the occipital cortex and region of the posterior thalamus dominated the subjects averaged brain activation. During the transition from wakefulness to sleep onset, this activation pattern changed to one showing greater activation in the right frontal cortex and region of the anterior thalamus. During stage 1 sleep, maximum activity was primarily in brain regions near the anterior thalamus.

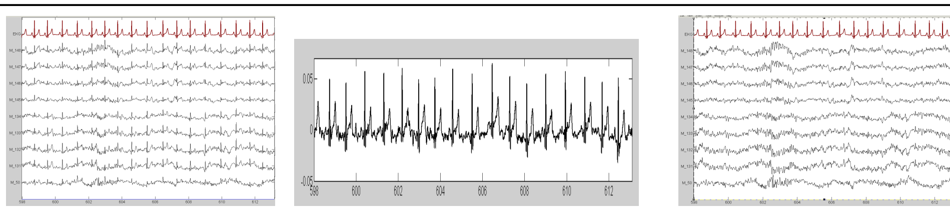

Fig. 2 Left, ECG and MEG data containing extensive heart artifact. Center, ICA heart artifact component extracted from MEG data. Left, MEG data with heart artifact removed.

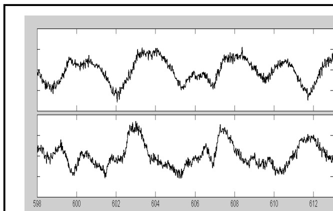

Fig. 3 Respiration and eye movement artifact extracted using 2^{nd} order ICA technique.

DISCUSSION

We have successfully developed a combination of second and fourth order ICA techniques that have enabled the systematic study of change in brain activity related to falling asleep. In addition we have found these technique useful for analysis of spontaneous epilepsy data and complex task performance data, such as vehicle driving tasks. In addition, to facilitate the widespread use of these technique we are developing user interfaces and automated procedures for both ICA data cleaning and imaging.

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