A state space approach to multimodal integration of simultaneously recorded EEG and fMRI

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A STATE SPACE APPROACH TO MULTIMODAL INTEGRATION OF SIMULTANEOUSLY 
RECORDED EEG AND FMRI

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ABSTRACT

We develop a state space approach to multimodal integration of simultaneously recorded EEG and fMRI. The EEG is represented with a distributed current source model using realistic MRI-based forward models, whose temporal evolution is governed by a linear state space model. The fMRI signal is similarly modeled by a linear state space model describing the hemodynamic response to underlying EEG current activity. We explore the feasibility of high dimensional dynamic estimation of simultaneous EEG/fMRI using simulation studies of the alpha wave.

Index Terms— EEG, fMRI, Multimodal Imaging

1. INTRODUCTION

The multimodal approach to functional brain imaging attempts to combine the unique attributes of different imaging modalities to provide a composite analysis with improved spatial and temporal resolution. Electroencephalogram (EEG) and magnetoencephalogram (MEG) observe the electric and magnetic fields at the scalp that originate from post-synaptic neuronal currents. Source localization estimates from EEG and MEG have high temporal resolution, on the order of milliseconds, but have a relatively low spatial resolution, on the order of centimeters. Functional magnetic resonance imaging (fMRI) observes a blood oxygen level dependent (BOLD) change in blood flow and volume that results from neuronal activity. BOLD fMRI has high spatial resolution, on the order of millimeters, but has relatively low temporal resolution due to the slow neurovascular response, on the order of seconds. Attempts to analyze these multimodal data have used thresholded fMRI statistical maps as a spatial “prior” distribution, either within a Bayesian framework or by placing equivalent dipoles at the maxima of fMRI activation [1], ignoring temporal information within the BOLD fMRI signal. However, experimental methods have evolved to allow for simultaneous recordings of EEG and fMRI that allow the same underlying realization of brain dynamics to observed by both imaging modalities. These simultaneous multiple observations suggest that it may be possible to take advantage of the joint temporal information in both data sets to improve spatio-temporal resolution. One problem with this idea is that the temporal resolution of fMRI is much slower than that of EEG, limiting the extent to which the two processes may coincide in time and frequency. However, experiments with concurrent EEG and fMRI [2, 3], as well as concurrent local field potentials (LFP), multi-unit activity (MUA) and fMRI [4], demonstrate that it is indeed possible to observe strong temporal correlations between measures of electrical activity and fMRI.

Dynamic analyses have been successfully applied to EEG/MEG data, as well as fMRI data. A major challenge in both cases is the high-dimensionality of the data and the underlying state space, a problem that is exacerbated with simultaneous EEG/fMRI data since the observation and state spaces must represent both data sets and dynamic processes. We have previously developed high-dimensional dynamic solutions to the MEG inverse problem [5, 6]. In this paper, we develop a state-space approach to multimodal integration of simultaneously recorded EEG and fMRI. We employ a distributed source model of EEG using a realistic MRI-based forward model, with random-walk temporal dynamics linked to a linear representation of the BOLD fMRI signal. We examine the feasibility of dynamic estimation of this high-dimensional state space through a simulation study of simultaneous EEG/fMRI of the alpha wave.

2. METHODS

2.1. State-Space Model for Simultaneous EEG/fMRI

In the EEG portion of an EEG/fMRI experiment, we obtain a recording of the electric potential from electrodes located on the scalp. For \( N \) large, assume that the data are sampled at times \( t \Delta \) for \( t = 1, \ldots, N \), with a sampling interval of \( \Delta = 0.01 \) seconds. Let \( y^{EEG}(t \Delta) \) denote the EEG measurement at time \( t \Delta \) in sensor \( s = 1, \ldots, S \). We define
\[ y^{\text{EEG}}_t = \left[ y^{\text{EEG}}_{-t\Delta} \ldots y^{\text{EEG}}_{-t\Delta} \right]^T \] to be the \( S \times 1 \) observation vector for EEG at time \( \Delta \). We assume that there are \( M \) sources. Let \( x^{\text{EEG}}_m(t\Delta) \) denote the cortical source activity at time \( t\Delta \) at location \( m \), where \( m = 1, \ldots, M \). We define \( x^{\text{EEG}}_t = \left[ x^{\text{EEG}}_{-t\Delta} \ldots x^{\text{EEG}}_{-t\Delta} \right]^T \) as the \( M \times 1 \) EEG state vector representing a distributed current source model. The relationship between the EEG observations vector and the EEG state vector is given by the observation equation

\[ y^\text{EEG}_t = G^\text{EEG} x^\text{EEG}_t + v^\text{EEG}_t, \quad (1) \]

where \( G^{\text{EEG}} \) is an \( S \times M \) lead field matrix computed using a quasistatic approximation of the Maxwell’s equations [7], and \( v^\text{EEG}_t \) is the \( S \times 1 \) vector of zero mean Gaussian noise with covariance matrix \( C \) representing the background machine noise. We model the dynamics of \( x_t \) as a random walk

\[ x^\text{EEG}_t = x^\text{EEG}_{t-1} + w^\text{EEG}_t, \quad (2) \]

where \( w^\text{EEG}_t \) is a \( M \times 1 \) zero mean Gaussian noise vector with covariance matrix \( Q = \text{diag}(\sigma_1^2, \sigma_2^2, \ldots, \sigma_M^2) \). The initial value \( x_0 \) is assumed to be a Gaussian vector with mean \( \mu \) and covariance matrix \( \Sigma \). Equations (1) and (2) define the state-space model for EEG.

The dynamic model for fMRI must take into account the temporal smoothing introduced by convolving the electrophysiological source currents \( x^\text{EEG}_t \) with the BOLD hemodynamic response. The hemodynamic impulse response (or hemodynamic response function, HRF) is modeled as a gamma function

\[ h_t = (t\Delta / \tau) \exp(-t\Delta / \tau), \quad (3) \]

where \( \tau = 1.5 \) seconds is a time constant governing the slow evolution of the response. This form of the HRF can be represented equivalently at each cortical source location \( m = 1, \ldots, M \) with a 2-dimensional state-space equation

\[ x^{\text{fMRI},m}_t = \begin{bmatrix} q & 0 \\ 1 & q \end{bmatrix} x^{\text{fMRI},m}_{t-1} + \begin{bmatrix} (\Delta / \tau) \\ 0 \end{bmatrix} x^{\text{EEG},m}_t + \begin{bmatrix} 1 \\ 0 \end{bmatrix} w^{\text{fMRI},m}_t \quad (4) \]

where \( q = \exp(-\Delta / \tau) \), and with state noise \( w^{\text{fMRI}} \) and initial conditions defined similarly as above. We can then combine equations (1), (2), and (4) to arrive at a full state space model

\[ \begin{bmatrix} x^{\text{EEG}}_t \\ x^{\text{fMRI}}_t \end{bmatrix} = \begin{bmatrix} I^M & 0 \\ F^{\text{fMRI}} & F^{\text{fMRI}} \end{bmatrix} \begin{bmatrix} x^{\text{EEG}}_{t-1} \\ x^{\text{fMRI}}_{t-1} \end{bmatrix} + \begin{bmatrix} w^{\text{EEG}}_t \\ w^{\text{fMRI}}_t \end{bmatrix} \quad (5) \]

where \( I^M \) is the \( M \)-th order identity matrix, and where we define the matrices \( F^{\text{fMRI}} \) and \( F^{\text{fMRI}} \) as

\[ F^{\text{fMRI}} = I^M \otimes \begin{bmatrix} (\Delta / \tau) \\ 0 \end{bmatrix}, \quad F^{\text{fMRI}} = I^M \otimes \begin{bmatrix} q & 0 \\ 1 & q \end{bmatrix}. \quad (6) \]

Observations of fMRI occur at a slower time scale than the EEG observations, typically once every 2 seconds, which we model using a time-varying observation matrix

\[ G_t = \begin{bmatrix} G^{\text{EEG}}_t \\ G^{\text{fMRI}}_t \end{bmatrix} \]

when both fMRI and EEG are observed

\[ G_t = \begin{bmatrix} G^{\text{EEG}}_t \\ 0 \end{bmatrix} \]

when only EEG is observed

where the fMRI observations are given by \( G^{\text{fMRI}} = I^M \left[ \begin{array}{c} 1 \\ 0 \end{array} \right] \). This yields a full observation model

\[ \begin{bmatrix} y^{\text{EEG}}_t \\ y^{\text{fMRI}}_t \end{bmatrix} = G_t \begin{bmatrix} x^{\text{EEG}}_t \\ x^{\text{fMRI}}_t \end{bmatrix} + \begin{bmatrix} v^{\text{EEG}}_t \\ v^{\text{fMRI}}_t \end{bmatrix}. \quad (9) \]

2.2. Simulation Studies and Estimation

We employed simulation studies to investigate the feasibility of dynamic estimation under this model. We constrained the source locations to the cortical mantle with about 6-mm spacing between adjacent sources. We chose a region of interest (ROIs) in temporal lobe of the left hemisphere as shown in Figure 1. This ROI contains 290 sources. We restricted the dimensionality of the problem to reduce computational complexity, with the rationale that higher-order versions could be implemented later using high-performance computing resources as in [LONG]. We computed the lead field matrix for sources in the two ROIs with dipole orientations constrained to the normal of the cortical mantle assuming a 64-channel EEG montage.
The time course of the sources on each ROI was simulated as a 10-Hz sinusoidal oscillation over a period of 4 seconds in order to emulate a realistic MEG experiment:

\[ x_m(t\Delta) = \begin{cases} \sin(2\pi \times 10t\Delta) & \text{if } x_m \text{ is active} \\ 0 & \text{if } x_m \text{ is inactive} \end{cases} \]  

This 4-second signal was preceded by 4 seconds of baseline, and 12 seconds without activity, yielding a 20-second segment of current source activity that was passed through the fMRI dynamic and observation models. The active patch shown in Figure 1 has 20 sources. The observation equation (9) was then used to obtain the simulated EEG/fMRI recordings. The signal-to-noise ratio (SNR) was set to 5, a value typical for EEG measurements, with signal amplitudes scaled uniformly across the active regions to achieve this SNR. Estimation is performed using the Kalman filter.

3. RESULTS AND DISCUSSION

Figures 2 shows the source current estimates estimated using the Kalman filter. Figure 3 shows the time course from a voxel within the active patch. These results illustrate that the algorithm is able to recover both the spatial and time course information within the simulated signal.

4. CONCLUSIONS AND FUTURE WORK

We have developed a state space approach for multimodal integration of simultaneous EEG and fMRI, and have and demonstrated in simulation studies that it is possible to recover both spatial and time course information from Kalman filter estimates under this model. Our future studies will extend these methods to allow estimation of parameters within the state space model, expand the source models to include the entire cortical surface, and examine performance of these methods on experimental data from human subjects.

5. REFERENCES


