



Abstract

Functional MRI (fMRI) has complementary spatiotemporal resolution compared to Electroencephalography (EEG) as well as Magnetoencephalography (MEG). Thus, their integrated analysis should improve the overall resolution. To integrate analysis of E/MEG and fMRI, we extend our previously proposed integrated E/MEG and fMRI neural mass model to a multi-area model by defining two types of connections: the Short-Range Connections (SRCs) between minicolumns within the areas and Long-Range Connections (LRCs) between inter-areas minicolumns. The nonlinear input/output relationship in the proposed model is derived from the state space representation of the multi-area model. For a given external stimulus, different possible multi-area models can be considered in which the number of areas, configuration and strength of connections between the areas are different. For selecting the best model as well as estimating its parameters, we propose the variational Bayesian expectation maximization (VBEM) method to iteratively optimize a lower bound on the marginal likelihood. The efficiency of the proposed method is illustrated using simulations. Overall, this work proposes an effective method to integrate E/MEG and fMRI and hopes to more effectively use these techniques in functional neuroimaging.

1. Introduction

- There are limited studies on integrated E/MEG and fMRI modeling in the literature [1-6] as summarized below.
- Riera, et al. [4,5]:
 - Proposed a two-dimensional autoregressive model with exogenous variables to describe the relationship between synaptic activity and hemodynamics [4].
 - Proposed a biophysically integrated model based on coupling canonical neuronal mass and expandable vasculature [5].
- Sotero and Trujillo-Barreto [6]:
 - Proposed integrated EEG/fMRI neural mass model based on short range and long range connections of active voxels.
 - There is a large number of active voxels and thus the proposed dynamical model has extensive computational load.
- We introduced two integrated E/MEG and fMRI models [1,2]:
 - A stochastic integrated model based on different aspects of postsynaptic potentials [1]
 - An integrated model based on the connections of the cortical minicolumns within one cortical area [2] (Fig. 1)
- In the current study:
 - The integrated model in [2] is extended from one cortical area to a multi-area model.
 - Variational Bayesian expectation maximization (VBEM) method is proposed to estimate parameters of the model.

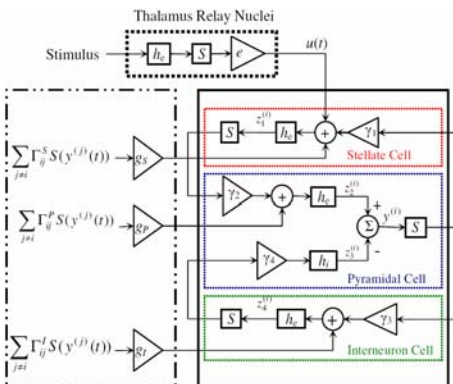


Fig 1. Illustration of the connections related to the i th minicolumn [2]. The left dash-dot box illustrates contributions of the neighboring minicolumns to the i th minicolumn.

2. Multi-Area Integrated model

- To extend the integrated model in [2] to a multi-area model:
 - Two connection types are introduced (Fig. 2):
 - Short-Range Connections (SRCs) between minicolumns within the area
 - Long-Range Connection (LRCs) between inter-area minicolumns
- Following equation shows dynamics of a multi-area model which contains N cortical areas and each area contains L minicolumns.

$$\begin{cases} \dot{X}_{\text{Area } i} = A_i X + [A_2 + (G^e \otimes I_{\text{src}, \text{src}})] A_3 + (G^l \otimes I_{\text{src}, \text{src}}) A_4 | S(X) + Bu + w \\ y_{\text{ECDs}} = CX \\ K_n = \sum_{i=1}^L (|x_3^{(i)}| + |x_5^{(i)}| + |x_7^{(i)} - x_6^{(i)}| + |x_7^{(i)}|) ; n=1,2,\dots,N \end{cases}$$

where G^e and G^l represent SRCs and LRCs parameters of the model, respectively.

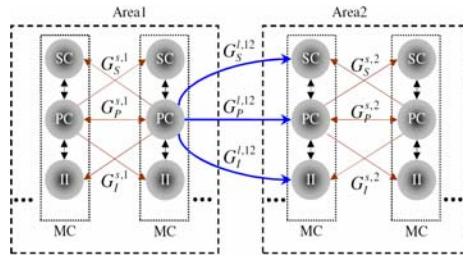


Fig 2. Illustration of the SRCs and LRCs in a two-area model. Within each area, pyramidal cells (PC) of all minicolumns affect the three cell populations (SC, PC, and II) of other minicolumns as SRC (brown arrows). Pyramidal cells of minicolumns of Area1 affect the three cell populations of all minicolumns in area2 as LRC (blue arrows). SC: Stellate Cells; PC: Pyramidal Cells; II: Inhibitory Interneurons; MC: Minicolumn.

3. Estimation of the Model Parameters

- Variational Bayesian Expectation Maximization Algorithm:
 - An iterative algorithm to maximize the marginal likelihood. Each iteration of VBEM method contains following two steps.
 - VB-E step (extended Kalman smoother):

$$q_{x_i}^{(k+1)}(x_i) \propto f(x_i, y_i) e^{-\bar{\Phi}^T \cdot z(x_i, y_i)} = p(x_i | y_i, \bar{\Phi}^{(k)}) \quad \forall i=1, \dots, n$$

$$\bar{\Phi}^{(k)} = \int d\theta q_{\theta}^{(k)}(\theta) \Phi(\theta)$$
 - VB-M step:

$$q_{\theta}^{(k+1)}(\theta) \propto h(\tilde{\eta}, \tilde{v}) g(\theta)^{\tilde{v}} e^{\Phi(\theta)^T \tilde{v}} ; \tilde{\eta} = \eta + n$$

$$\tilde{v} = v + \sum_{i=1}^n \bar{z}(y_i) ; \bar{z}(y_i) = \langle u(x_i, y_i) \rangle_{q_{x_i}^{(k+1)}(x_i)}$$
- Estimation of the Model Parameters:
 - Preprocessing of the E/MEG and fMRI data to find active areas and their locations.
 - Using VBEM method to estimate parameters of the model.

4. Simulation Results

- A three area model is simulated in which each area contains four minicolumns (Fig. 3).
- 12 parameters are estimated:
 - Six parameters of the SRCs
 - Six parameters of the LRCs
- Fig. 4 illustrates the simulation results.

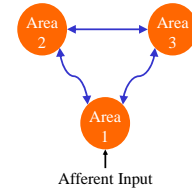


Fig 3. Illustration of the LRCs in the three area model used in the simulation. The SRCs between minicolumns within the areas are not shown.

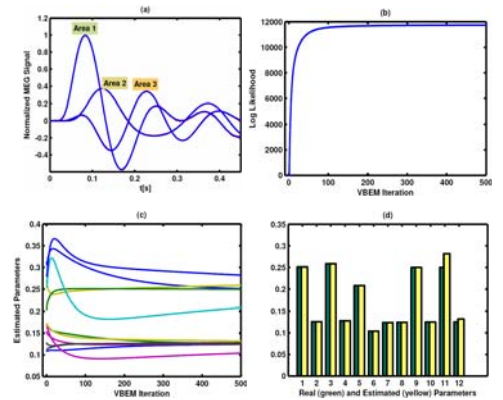


Fig 4. Simulation results of a three area model. (a) Normalized real (red) and Estimated (blue) MEG Signals. (b) Log-likelihood of the estimation. (c) Trends of converging the estimated parameters to their final values. (d) Real (green) and estimated (yellow) values of the parameters.

5. Conclusions

- A multi-area integrated E/MEG and fMRI neural mass model is proposed.
- The nonlinear input/output relationship in the proposed model is derived from the state space representation of the multi-area model.
- The variational Bayesian expectation maximization (VBEM) method is proposed to estimate parameters of the model as well as activation detection in the areas.
- This study proposes an effective method to integrate E/MEG and fMRI for more effective use of these techniques in functional neuroimaging.

6. References

- A. Babajani, et al., *Brain Topography*, vol. 18, No. 2, pp. 101-113, 2005.
- A. Babajani and H. Soltanian-Zadeh, *Biomed. Eng.*, vol. 53, pp. 1794-1801, 2006.
- J. Daunizeau, et al., *Neuroimage*, vol. 36, pp. 69-87, 2007.
- J. J. Riera, et al., *Philos Trans R Soc Lond B Biol Sci*, vol. 360, pp. 1025-41, 2005.
- J. J. Riera, et al., *Hum Brain Mapp*, vol. 27, pp. 896-914, 2006.
- R. C. Sotero and N. J. Trujillo-Barreto, *Neuroimage*, vol. 39, pp. 290-309, 2008.