EEG-FMRI FUSION OF NON-TRIGGERED DATA USING KALMAN FILTERING

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1. ABSTRACT

We present a method to combine simultaneous acquisitions of EEG and fMRI measures for estimating ongoing cortical activity. We do not assume that the activity is linked to any repeated stimulation. Rather we solve a very large inverse problem, where EEG and fMRI are noisy measures of the unknown underlying neural activity, and are related to it via realistic physiological models. An extended Kalman filter is used to estimate neural activity from the combined measurements at all instants and all cortical locations. Actually it is already an interesting tool for analyzing EEG or fMRI acquisition in isolation since it is able to handle common difficulties with the temporal aspect of both modalities (temporal smoothness in the EEG inverse problem, and hemodynamic deconvolution in fMRI). Its application to simulated data shows how it takes advantage of EEG high temporal resolution and fMRI spatial precision when reconstructing sources activity.

2. INTRODUCTION

Recent studies have proved that activation in fMRI can be detected for non-repeated activities, like viewing a movie [1], thus opening the door to trial by trial investigations of cortical activity instead of using evoked potentials or models triggered by a repetitive stimulation. In this context, the possibility to acquire simultaneously EEG and fMRI signals [2] increases the power of cortical activity estimation: the EEG signal is known to bring a much better temporal resolution than fMRI, and it also carries some spatial information if one solves an inverse problem.

Horwitz et al. [3] give an overview of different attempts to combine EEG and fMRI datas. Most existing methods [4, 5] do combine the two measures in terms of estimated intensity of the cortical sources, but do not take into account the temporal aspect of acquisition (and thus do not take advantage of the possibility to acquire data simultaneously). Lahaye et al. [6] proposed to use simultaneous EEG-fMRI data to estimate amplitude variations across trials.

Our approach is to use biophysiological models to relate both electrophysiological and hemodynamic measures to the neural activity [7, 8], thereby making possible to estimate the whole sources timecourses from multimodality measures. The mathematical framework is that of Kalman filtering, used by Riera et al. [9] in fMRI, to estimate hidden states time-courses.

3. FUSION MODEL

The main assumption of EEG-fMRI fusion is that both modalities do measure a common cortical activity \( u \), that we suppose to be the sum of electrical activities at the surface of the cortex. \( u \) is thus a spatiotemporal unknown variable representing the time course of \( n_s \) sources distributed on the cortex. However, the presence of cerebral activities detected by only one of the two modalities is permitted by the model, as we will see below.

Let us consider the EEG measure first. We note \( y_{\text{eeg}} \) the EEG signal and \( n_e \) the number of electrode. The EEG model is given by the Maxwell equations, that describe currents propagation from the cortical surface to the scalp [7]. Since the propagation times can be neglected, potentials at the electrodes tips at time \( t \) are linear functions of the vector of sources activities at the same time, \( u(t) \). We add a Gaussian noise that models the measure of activities not detected in fMRI, plus additional measurement and artefact noises:

\[
y_{\text{eeg}}(t) = Bu(t) + \eta_{\text{eeg}}(t),
\]

where \( B \) is the \( n_e \times n_s \) forward problem matrix, and \( \eta_{\text{eeg}}(t) \sim N(0, \Sigma_{\text{eeg}}) \).
Let us now note \( y_{\text{fMRI}} \) the BOLD signal. Its dynamic is described by a biophysiological dynamical system. We use the Buxton Balloon Model [8] as formulated by Friston et al. in [10]. This model describes the effects of neural activity on blood flow, venous blood volume, venous deoxyhemoglobin contents and at last BOLD signal. We suppose that the hemodynamic effects related to each cortical source are independent and take place at the same location as the corresponding source. This allows us to describe the fMRI time course at location \( s \) independently for each source, as the output of a stochastic dynamical system:

\[
\begin{align*}
\dot{x}(s,t) &= f(x(s,t), u(s,t)) + \xi_{\text{fMRI}}(s,t) \\
y_{\text{fMRI}}(s,t) &= g(x(s,t)) + \eta_{\text{fMRI}}(s,t),
\end{align*}
\]

(2)

where \( x(s,t) \) is the hemodynamic state at location \( s \) and time \( t \) (its dimension is 4 for the model we use), and \( \xi_{\text{fMRI}} \) and \( \eta_{\text{fMRI}} \) are Gaussian evolutive and measurement noises, \( \xi_{\text{fMRI}}(s,t) \sim \mathcal{N}(0, Q_{\text{fMRI}}) \) and \( \eta_{\text{fMRI}}(s,t) \sim \mathcal{N}(0, \sigma^2_{\text{fMRI}}) \). Evolutive noise \( \xi_{\text{fMRI}} \) implicitly takes into account cortical activities not detected in EEG.

In order to get a posteriori probabilities on the sources time courses \( u \) with the Kalman filter, we need to set a priori probabilities on them. We choose to use the simple autoregressive model:

\[
\hat{u}(t) = u(t) + \xi_u(t),
\]

(3)

where \( \xi_u \) is a Gaussian evolutive noise \( \xi_u(t) \sim \mathcal{N}(0, Q_u) \).

The spatial correlation matrix between sources \( Q_u \) is constructed according to geometrical constraints, to ensure spatial smoothness of the cortical activity. Temporal smoothness is ensured by the autoregression, and can be regulated through the diagonal terms in \( Q_u \).

4. ALGORITHM

The whole model described above can be expressed as a single nonlinear dynamical system, which we write in discrete form:

\[
\begin{align*}
X_{k+1} &= F(X_k) + \xi_k \\
Y_k &= G(X_k) + \eta_k,
\end{align*}
\]

(4)

\( X_k \) is the set of hidden state variables (sources activities \( u \) and hemodynamics states \( x \)) of all sources at instant \( k \), concatenated in a single vector.

\( F \) gathers the evolution equations in (2) and (3).

\( Y_k \) is the set of measurements (EEG signals at all electrodes and/or fMRI signals at all sources locations), concatenated in a single vector. Since there are much less acquisition times in fMRI than in EEG, we interpolate the fMRI time course to all EEG instants using a linear interpolation.

\( G \) gathers the measurement equations in (1) and (2).

At last, \( \xi_k \) and \( \eta_k \) are Gaussian evolutive and measurement noises, \( \xi_k \sim \mathcal{N}(0, Q) \) and \( \eta_k \sim \mathcal{N}(0, R) \); their variances are calculated from the values of \( Q_u \), \( \Sigma_{\text{eeg}} \), \( Q_{\text{fMRI}} \) and \( \sigma^2_{\text{fMRI}} \).

Given the measure \( Y \), we can estimate the hidden state \( X \) (and in particular \( u \), the neural activity detected by EEG and fMRI) recursively for increasing times, by using an extended Kalman filter [11, 12]: if both evolutive and measure noises are Gaussian, and if at each sampling instant the nonlinear evolution and measure functions are approximated up to first order, then the a posteriori distribution of the hidden states is also Gaussian: the Kalman filter calculates the mean and variance of this distribution.

To be strictly accurate, the estimation of hidden states at instant \( k \) given by the Kalman filter does not take into account measures after instant \( k \). It calculates the following means and variances:

\[
\begin{align*}
\hat{X}_k &= E(X_k | Y_1 \ldots Y_k) \\
P_k &= E(X_k X_k^T | Y_1 \ldots Y_k).
\end{align*}
\]

Then, it is necessary to apply a Kalman smoother [11] to obtain the final a posteriori distribution:

\[
\begin{align*}
\hat{X}_T &= E(X_k | Y_1 \ldots Y_T) \\
P_T &= E(X_k X_k^T | Y_1 \ldots Y_T),
\end{align*}
\]

where \( T \) is the number of instants.

Details of the Kalman filter and smoother are given in the appendix.

5. ARTIFICIAL DATA

We present simulation results, using a realistic head model based on the segmentation of anatomical MRI data. The number of sources on the cortex is currently limited by memory.
Fig. 3. *Estimated cortical activity* when using the Kalman filter estimation on EEG and fMRI measures, both separately and together. Left: estimated cortical sources time courses. Right: estimated activities at two specific instants are mapped onto the cortex.

Fig. 4. *Estimated time courses* of a few cortical sources are shown, and compared to their true values. Top: (left) fMRI alone was able to detect a spread out activity of an actually activated source; the fusion estimation is slightly more focal, but cannot violate more the smoothness constraint; (right) the inverse situation: EEG found activation in a non-activated source, and fMRI turns down this estimation. Bottom: (left) a typical example of how fMRI alone recovers the low frequency fluctuations, whereas EEG brings a complementary information on fast variations. (right) here, EEG was unable to give any information on the source activity; fusion estimation is then the same as that of fMRI alone.

The respective qualities of EEG and fMRI in term of temporal and spatial resolutions are clearly illustrated. Indeed, in the EEG estimation, the temporal pattern of activation peak around t=8.5s is recovered exactly, but its localisation is quite diffuse (more sources are activated than in the original data, and the activation power is reduced). On the other hand, in the fMRI estimation, it is the estimated time course that is diffuse, whereas the method found the right activation focus. The fusion algorithm then finds a compromise between the two estimations, and the smoothness of neural sources time courses. It was not able to find the exact amplitude of the activity peak as in figure 2, but this is not surprising since the algorithm used an a priori auto-regressive model for sources activity (equation (3)), that supposes a temporal smoothness.

Figure 4 shows the estimated time courses of a few cortical sources with different characteristics. When it is applied to fMRI only, the Kalman filter performs a deconvolution of the BOLD signal for each source location, that leads to a quite accurate estimation already (center row in figure 3 and cyan time courses in figure 4). Compared to it, the EEG estimation (top row in 3 and green time courses in 4) is much worse, due to the ill-posedness of the inverse problem. However, in the fusion context (bottom row in 3 and red time courses in 4), EEG brings a complementary information in terms of rapid fluctuations, leading to a better estimation of ongoing neural activity.

6. RESULTS

The current version of the algorithm can work with EEG or fMRI measures alone, or with both of them simultaneously. To emphasize the improvement brought by the fusion, we first ran the algorithm on each modality separately. Figure 3 shows the results for EEG, fMRI and EEG+fMRI estimations.

7. CONCLUSION

Our work illustrates how information coming from simultaneous EEG and fMRI measures can be integrated together to
obtain a better estimation of the underlying neural activity. Applied to the EEG alone, the Kalman filter technique solves an inverse problem that constrains the cortical sources to be smooth in time. Applied to fMRI alone, it performs a signal deconvolution. Applied to both simultaneously, it integrates temporal and spatial aspects of each modality, and takes advantage of their respective qualities.

In our simulation data, it was particularly efficient to estimate neural "background activity". It could thus open the door to neural activity estimations without averaging over repetitions of a same stimulation.

We are currently using the method on simultaneous EEG and fMRI acquisition on epileptic subjects, which will allow us also to test and possibly correct the model main hypothesis: the existence of a common neural activity that underpins EEG and fMRI measurements, and the actual link between the time courses of the electrical activity implied in EEG and the metabolic energy demand implied in fMRI.

8. APPENDIX

The Kalman filter [11, 12] is a recursive algorithm that alternatively computes the distribution of $X_k$ given measures before instant $k$ (evolution update step) and given measures until instant $k$ (measure update step), starting with the known a priori distribution of $X_0$ ($X_1^0$ and $P_1^0$). It requires a local linearization of the dynamical system at each instant.

Evolution update:

\[
\dot{X}_k^{k-1} = \text{E}(X_k | Y_1 \ldots Y_{k-1}) = F(X_{k-1}^{k-1})
\]

\[
P_k^{k-1} = \text{E}(X_kX_k^T | Y_1 \ldots Y_{k-1}) = AP_k^{k-1}A^T + Q,
\]

where $A = \frac{\partial F}{\partial X}(X_{k-1}^{k-1})$.

Measure update:

\[
K = P_k^{k-1}C^T(CP_k^{k-1}C^T + R)^{-1}
\]

\[
\dot{X}_k^k = \dot{X}_k^{k-1} + \dot{K}(Y_k - G(X_{k-1}^{k-1}))
\]

\[
P_k^k = P_k^{k-1} - KP_k^{k-1}CT
\]

where $C = \frac{\partial G}{\partial X}(X_{k}^{k-1})$.

After the Kalman filter forward pass, the Kalman smoother performs a backward pass, starting at $k = T - 1$:

\[
J = P_k^k A^T(P_{k+1}^{k+1})^{-1}
\]

\[
\dot{X}_T^T = \dot{X}_T^k + J(X_{k+1}^T - \dot{X}_k^k)
\]

\[
P_T^T = P_k^k + J(P_{k+1}^T - P_{k+1}^k)JT,
\]

where $A = \frac{\partial F}{\partial X}(X_{k+1}^T)$.

9. REFERENCES


