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***EEG-fMRI fusion of non-triggered data using
Kalman filtering***

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Thème BIO



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EEG-fMRI fusion of non-triggered data using Kalman filtering

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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.

Key-words: fusion, EEG, fMRI, Kalman filter

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Fusion de décours temporels EEG et IRMf avec le filtre de Kalman

Résumé : Nous présentons une méthode pour combiner des acquisitions simultanées en Electroencéphalographie (EEG) et Imagerie par Résonance Magnétique fonctionnelle (IRMf), en termes d'estimation de l'activité cérébrale sous-jacente. Nous n'estimons pas la réponse à une stimulation particulière répétée au cours d'une expérience, mais le décours temporel de l'activité tout au long de l'acquisition. Cela revient à résoudre un problème inverse de dimensionnalité très importante, où l'EEG et l'IRMf sont des mesures bruitées de l'activité neuronale inconnue, à laquelle elles sont reliées par des modèles physiologiques. Nous utilisons un filtre de Kalman étendu pour estimer cette activité en tout instant et en tout point du cortex. Cet outil d'ailleurs se révèle aussi intéressant pour l'analyse de données EEG ou IRMf seules, car il est capable d'intégrer les aspects temporels, en général difficiles à exploiter, des deux modalités (prise en compte d'une continuité temporelle en EEG, et réalisation d'une déconvolution de la réponse hémodynamique en IRMf). Son application sur des données synthétiques montre qu'il tire parti des qualités respectives de l'EEG et de l'IRM (bonnes résolutions respectivement temporelle et spatiale).

Mots-clés : fusion, EEG, IRMf, filtre de Kalman

1 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 estimation power of cortical activity: the EEG signal is known to bring a much better temporal resolution to 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 accross 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 timecourses.

2 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 only is permitted by the model, as we will see below.

Let us consider the EEG measure first. We note y_{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:

$$y_{\text{eeg}}(t) = Bu(t) + \eta_{\text{eeg}}(t), \quad (1)$$

where B is the $n_e \times n_s$ forward problem matrix, and $\eta_{\text{eeg}}(t) \sim \mathcal{N}(0, \Sigma_{\text{eeg}})$.

Let us now note y_{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

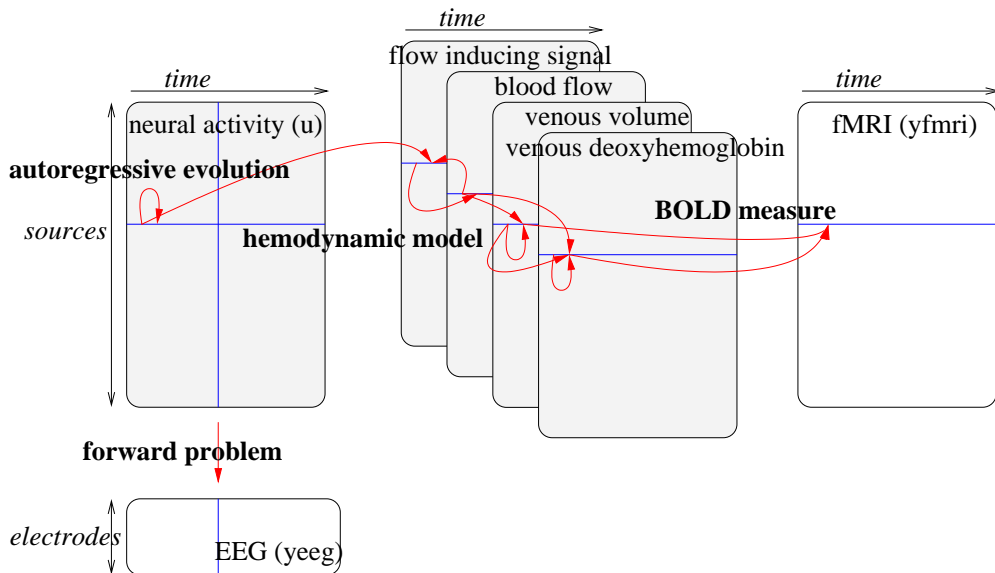


Figure 1: *Fusion model*. EEG measure is described by the forward problem, while a physiological dynamical system involving neural activity and hidden hemodynamic quantities underlies fMRI measure. Our fusion algorithm estimates the whole spatio-temporal time courses of neural activity, but also of all hemodynamic variables.

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:

$$\begin{cases} \dot{x}(s, t) &= f(x(s, t), u(s, t)) + \xi_{\text{fmri}}(s, t) \\ y_{\text{fmri}}(s, t) &= g(x(s, t)) + \eta_{\text{fmri}}(s, t), \end{cases} \quad (2)$$

where $x(s, t)$ is the hemodynamic state at location s and time t (its dimension is 4 for the model we use), and ξ_{fmri} and η_{fmri} are Gaussian evolutive and measurement noises, $\xi_{\text{fmri}}(s, t) \sim \mathcal{N}(0, Q_{\text{fmri}})$ and $\eta_{\text{fmri}}(s, t) \sim \mathcal{N}(0, \sigma_{\text{fmri}}^2)$. Evolutive noise ξ_{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:

$$\dot{u}(t) = u(t) + \xi_u(t), \quad (3)$$

where ξ_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 .

3 Algorithm

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

$$\begin{cases} X_{k+1} &= F(X_k) + \xi_k \\ Y_k &= G(X_k) + \eta_k, \end{cases} \quad (4)$$

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, ξ_k and η_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 , Σ_{eeg} , Q_{fmri} and σ_{fmri}^2 .

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:

$$\begin{aligned} \hat{X}_k^k &= E(X_k | Y_1 \dots Y_k) \\ P_k^k &= E(X_k X_k^T | Y_1 \dots Y_k). \end{aligned}$$

Then, it is necessary to apply a Kalman smoother (11) to obtain the final a posteriori distribution

$$\begin{aligned} \hat{X}_k^T &= E(X_k | Y_1 \dots Y_T) \\ P_k^T &= E(X_k X_k^T | Y_1 \dots Y_T), \end{aligned}$$

where T is the number of instants.

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

4 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

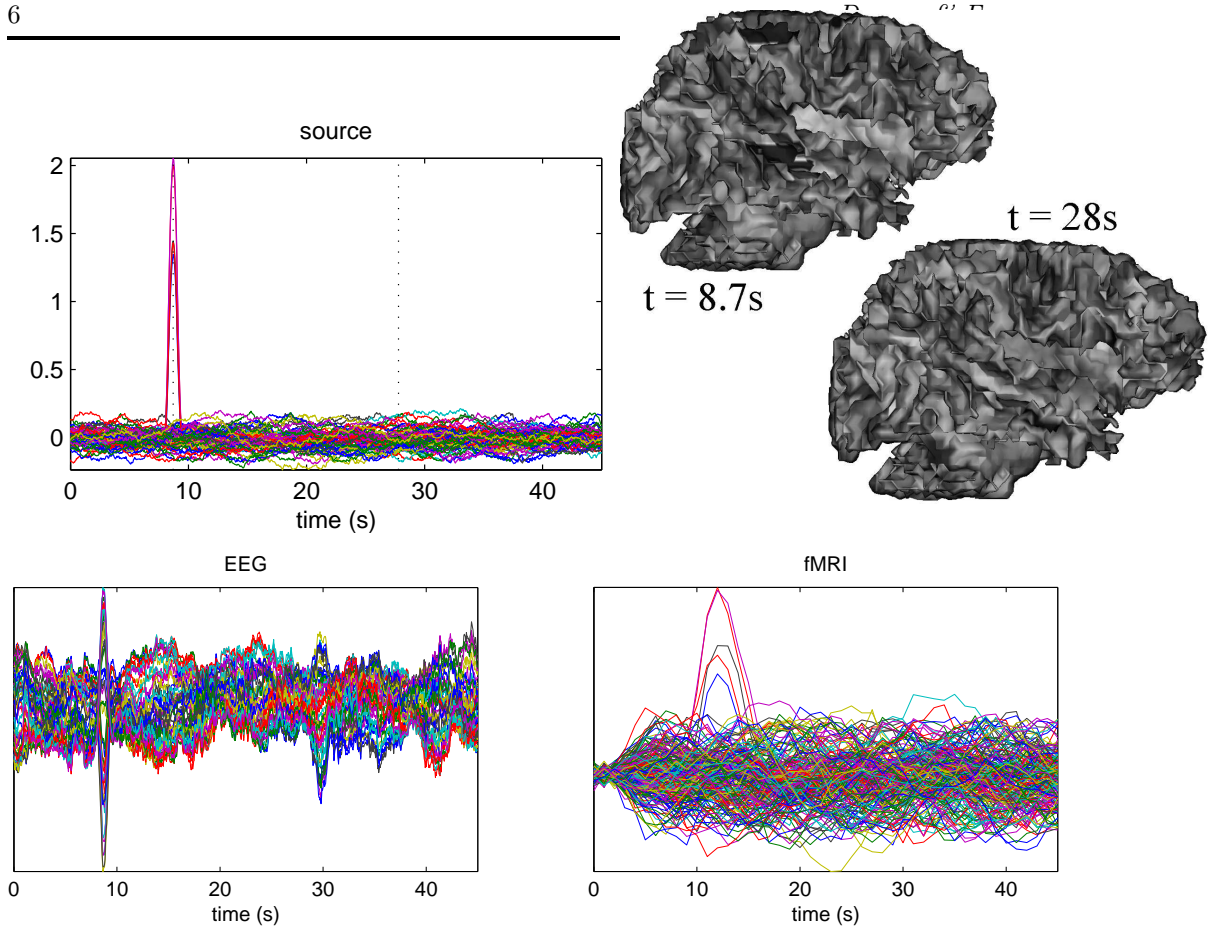


Figure 2: *Artificial data.* Top: (left) plot of the time courses of all cortical sources; neural activity was generated according to the evolutive model (3) and a rapid burst (1s half width) was added to a few sources; (right) activity mapped on the cortex at instants represented by dotted vertical lines. Bottom: EEG and fMRI measures generated by the forward problem (1) and the Balloon Model (2).

constraints: indeed, the hidden-states dimension in the model (the length of vector \hat{X}_k) is equal to the number of sources n_s times the number of variables for one source (u and 4 hemodynamic variables in x), and the algorithm uses square matrices of this size (P_k^{k-1} , P_k^k , J ... see appendix). Thus we use a model with 1000 sources on the cortex. Our decimation method allows us to interpolate between these 1000 sources and the 45000 vertices of the cortex full mesh, from which we construct the EEG forward problem matrix B in (1). We used a set of 64 electrode locations on the scalp.

We simulated cortex activity according to the evolutive model (3), and added some wave signals to a few chosen sources, to test the model ability to handle fast and strong variations.

Then the EEG and fMRI signals were simulated according to the models ((1) and (2)), see figure 2. Physiological parameters were assigned plausible values (10).

5 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. The respective qualities of EEG and fMRI in terms 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 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,

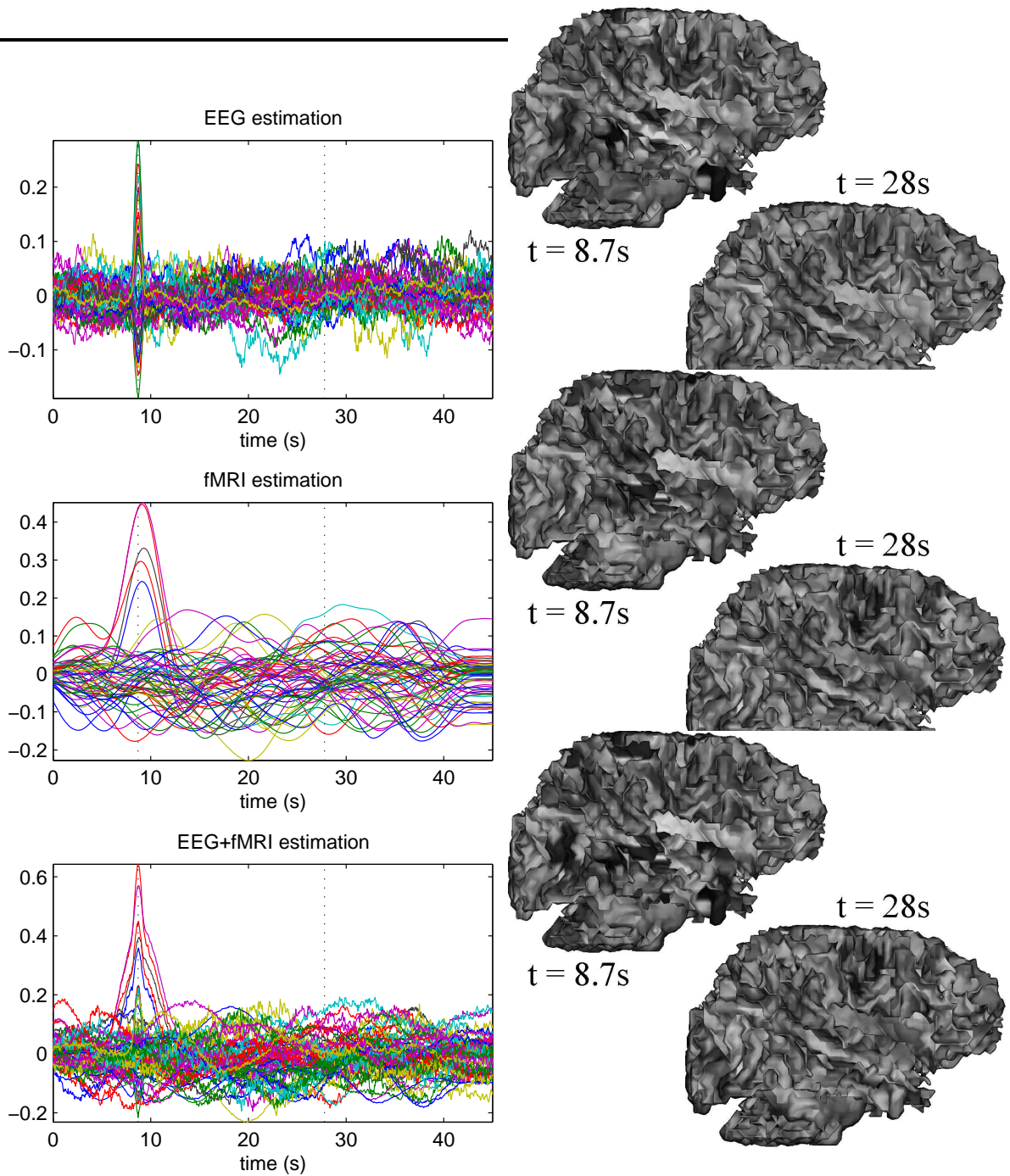


Figure 3: *Estimated cortical activity* when using the Kalman filter estimation on EEG and fMRI measures, both separately and together. Left: estimated cortical sources time courses. Right: estimated activities at two specific instants are mapped onto the cortex.

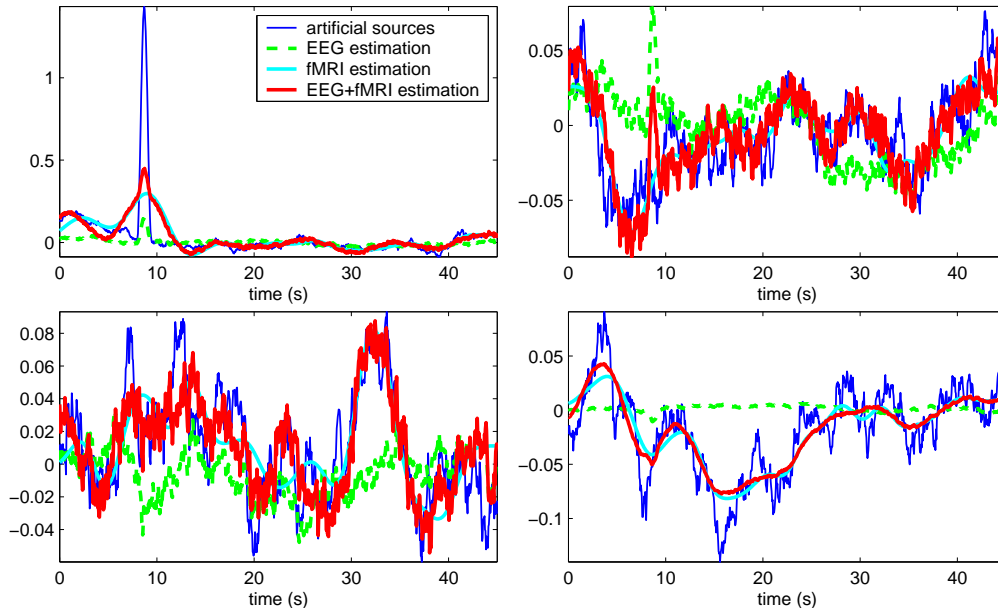


Figure 4: *Estimated time courses* of a few cortical sources are shown, and compared to their true values. Top: (left) fMRI alone was able to detect a spread out activity of an actually activated source; the fusion estimation is slightly more focal, but cannot violate more the smoothness constraint; (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.

and the actual link between the electrical activity implied in EEG and the metabolic energy demand implied in fMRI.

7 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 (\hat{X}_1^0 and P_1^0). It requires a local linearization of the dynamical system at each instant.

Evolution update:

$$\begin{aligned} \hat{X}_k^{k-1} &= E(X_k | Y_1 \dots Y_{k-1}) &= F(\hat{X}_{k-1}^{k-1}) \\ P_k^{k-1} &= E(X_k X_k^T | Y_1 \dots Y_{k-1}) &= A P_{k-1}^{k-1} A^T + Q, \end{aligned}$$

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

Measure update:

$$\begin{aligned} K &= P_k^{k-1} C^T (C P_k^{k-1} C^T + R)^{-1} \\ \hat{X}_k^k &= \hat{X}_k^{k-1} + K (Y_k - G(\hat{X}_k^{k-1})) \\ P_k^k &= P_k^{k-1} - K C P_k^{k-1}, \end{aligned}$$

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

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

$$\begin{aligned} J &= P_k^k A^T (P_{k+1}^k)^{-1} \\ \hat{X}_k^T &= \hat{X}_k^k + J (\hat{X}_{k+1}^T - \hat{X}_{k+1}^k) \\ P_k^T &= P_k^k + J (P_{k+1}^T - P_{k+1}^k) J^T, \end{aligned}$$

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

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