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Topography-Time-Frequency Atomic Decomposition for Event-Related M/EEG Signals

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Abstract— **We present a method for decomposing MEG or EEG data (channel $\times$ time $\times$ trials) into a set of atoms with fixed spatial and time-frequency signatures. The spatial part (i.e., topography) is obtained by independent component analysis (ICA). We propose a frequency prewhitening procedure as a pre-processing step before ICA, which gives access to high frequency activity. The time-frequency part is obtained with a novel iterative procedure, which is an extension of the matching pursuit procedure. The method is evaluated on a simulated dataset presenting both low-frequency evoked potentials and high-frequency oscillatory activity. We show that the method is able to recover well both low-frequency and high-frequency simulated activities. There was however cross-talk across some recovered components due to the correlation introduced in the simulation.**

I. Introduction

Electroencephalogram (EEG) and magnetoencephalogram (MEG) data are by nature two-dimensional signals, across space (EEG electrodes or MEG sensors) and time. These signals are generated by brain sources, with complex spatio-temporal dynamics. It can be useful to separate these signals into spatial patterns (or 'topographies'), and temporal time courses, either in the framework of dipolar source localization or of blind source analysis. So far, most studies have concerned event-related potentials, which are rather slow-varying events (< 20 Hz). More recently, it has been proposed to add the frequency dimension into the decomposition [1], as the M/EEG activity of interest can involve higher frequencies (in the gamma range, 35-100 Hz) that are revealed by time-frequency analysis [2].

We present here a decomposition into atoms with fixed spatial and time-frequency signatures. The spatial part is obtained by independent component analysis (ICA), in order to unmix activities (brain sources, artefacts) that overlap at the sensor level. The goal of ICA is to separate processes with different spatial signatures, and with time courses that are independent of one another [3]. For example, it has been demonstrated to be able to unmix different processes in an oddball paradigm [4].

We propose a novel frequency prewhitening procedure that enables the analysis of high frequency activity. Indeed, the high frequencies are hidden in the original signals because of the $1/f^\alpha$ structure of M/EEG data [5]. The time-frequency part is obtained with a novel iterative procedure, which bears similarities with the matching pursuit procedure [6], with an extension to data organized in trials.

We have tested the method on a simulated dataset, with a large number of components, which topographies and time-frequency structures are similar to results obtained in cognitive paradigms. We introduced some correlation between components in order to test the robustness of ICA to departure from the assumption of independence.

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II. Estimation of Atoms

We present here the details of the estimation of the topography-time-frequency atoms. The topographies are obtained by independent component analysis (ICA) on prewhitened data. For each topography, the time-frequency structure is obtained by an iterative search based on time-frequency analysis.

A. Frequency Prewhitening

Frequency prewhitening is performed in order to equalize the power in all frequency bands, thereby giving the ICA algorithm the possibility to separate high-frequency oscillatory activity from other activities. The signal $S(c,k,t)$ is composed of C channels, K trials and T time points per trial. We estimate the average spectrum $\widehat{S}$ across channels and trials by

$$spec(f) = \left(\frac{1}{CK} \sum_{c=1}^{C} \sum_{k=1}^{K} |\widehat{S}(c,k,f)|^2 \right)^{\frac{1}{2}}. \qquad (1)$$

with $\widehat{S} = FFT(S)$ fast Fourier transform of S.

A function β/f^α is fitted on the spectrum, in a given frequency band of interest $]0; f_1]$. The fit is performed with a robust estimator [7].

The complex Fourier transform at each frequency in the band $]0; f_1]$ is multiplied by f^α, followed by inverse Fourier transform. The prewhitened signal $\tilde{S}$ is therefore:

$$\tilde{S}(c,k,t) = FFT^{-1}(\widehat{S}(c,k,f) \cdot min(f, f_1)^\alpha/\beta)) \qquad (2)$$

with FFT^{-1} inverse Fourier transform.

B. Estimation of Topographies

The atom topographies are estimated by independent component analysis (ICA) performed on the prewhitened data. The ICA permits to separate processes with a fixed topography, maximizing the independence across component time-courses.

$$\tilde{S}(c,k,t) = \sum_{i=1}^{I} T_i(c) C_i(k,t). \quad (3)$$

$T_i(c), i = 1...I$, are topographies estimated by ICA on the data concatenated across trials. $C_i(k,t)$ are the temporal parts of the components. We use the infomax algorithm [8] as implemented in the EEGLAB toolbox [9], in the Matlab environment (Mathworks, Natick, MA).

In order to compare to another method for searching space-time-frequency patterns, we tested the PARAFAC method (N-way matlab toolbox, [10]) on the simulated data [1]. We used both a (channel $\times$ time $\times$ frequency $\times$ trial) array consisting of TF planes obtained with an analytical wavelet transform ($\xi = 7$), and on the mean array across trials (channel $\times$ time $\times$ frequency).

C. Iterative Time-Frequency Atom Search

For each component of interest $C_i(k,t)$, we search iteratively for a set of Gabor atoms $A_s^i(t)$, $s \in 1...S$ that fit best the data on average. The Gabor atoms have a gaussian enveloppe modulated in frequency; they are capable of modelling both low frequency event-related potentials and high frequency oscillations. Moreover, the Gabor atoms offer the best trade-off between time and frequency compactness.

At a given iteration s, the atom is found using a set of time-frequency transforms. The first iteration is performed on the data itself: $C_i^0(k,t) = C_i(k,t)$. Then, at each iteration s, the atom is subtracted from the data, leading to a new dataset $C_i^{s+1}(k,t)$.

In order to compute the time-frequency transforms, we use Morlet wavelets, which are a time-scale implementation of Gabor atoms. We have in the frequency domain:

$$\Psi_\sigma^\xi(f) = \frac{\sqrt{\sigma}}{(4\pi)^{\frac{1}{4}}} e^{-\frac{1}{2}(\sigma \cdot 2\pi f - \xi)^2} \quad (4)$$

The oscillation parameter ξ determines the number of periods of the wavelet. The time-support is proportional to σ and the oscillating frequency is equal to $\xi/(2\pi\sigma)$.

The time-frequency transform at iteration s is:

$$TF^s(t,\sigma,\xi) = \frac{1}{K} \sum_k |W_k^s(t - t_k, \sigma, \xi)|^2. \quad (5)$$

with W_k^s wavelet transform of trial k:

$$W_k^s(t,\sigma,\xi) = FFT^{-1}(\hat{C}_s(k,f)\Psi_\sigma^\xi(f)). \quad (6)$$

with $\hat{C}_s(k,f) = FFT(C(k,t))$.

As the activities of interest can either be transients (e.g., evoked potentials) or bursts of oscillations, we use a range of oscillation parameters $\xi \in \{1.5, 2, 5, 9, 25\}$, and compute an average map per ξ. The peak value across time, frequency and ξ's is found:

$$(t^s, \sigma^s, \xi^s) = argmax(TF^s(t,\sigma,\xi)) \quad (7)$$

This peak represents the Gabor atom which correlates best on average with the (time $\times$ trials) component data. At each triak, the Gabor atom is fitted on the actual data and subtracted, allowing some time-jitter in order to cope with inter-trial variability. This leads to a new set of trials $C_i^{s+1}(k,t)$ on which the above-described procedure can again be applied.

The number of iterations S is determined empirically; however, one could consider using a quantitative criterion, based for example on the energy of the residuals after subtraction. The main difference with matching pursuit resides in the use of the data over a collection of trials, thereby taking advantage of the information arising from reproducibility across trials.

D. Validation Data

We created a series of EEG trials with 5 simulated components, each simulated component based on one or two dipoles simulated in a 3-sphere volume conductor model. The time course of these sources consisted of a sum of Gabor atoms, presenting jitters in time, frequency and width across trials. The topographies of some of these sources were inspired by the findings of [2] and [11] on real data. The simulated components (SCs) were:

- SC1: two synchronous occipital dipoles (maximum at electrodes O1 and O2), with a positive wave around 100 ms (P100), a negative wave around 170 ms (N170) and an early gamma burst (40 Hz) around 100 ms.
- SC2: a parieto-occipital dipole (Pz-POz), with a late gamma burst (60 Hz) around 300 ms.
- SC3: one radial dipole (Cz-C4), with a gamma burst (40 Hz) around 100 ms.
- SC4: one radial dipole in the parietal region (Cz-Pz), with a negative wave around 100 ms (N100) and a positive wave between 250 and 400 ms (P300).
- SC5: a left frontal dipole, with a burst of gamma (45 Hz), around 150 ms.
- SC6: a right frontal dipole, with a burst of gamma (45 Hz), around 180 ms.

We introduced a negative correlation of 30% between the parameters of the P100 of SC1 and of the N100 of SC3, and 80% between the parameters of SC4 and SC5. This correlation was introduced in order to have a realistic behavior, departing from the idealized assumption of independence used in ICA. We also added simulated noise correlated in space and time. The spatial correlation of the simulated noise was obtained by placing dipoles uniformly on a grid inside a sphere, each with a random time-course (Gaussian distribution). The temporal correlation was obtained by filtering the data at each electrode with an AR model estimated on real EEG data. This ensured a realistic spectrum of the data, with a $1/f^\alpha$ profile, plus an alpha peak around 10 Hz, and a 50 Hz peak.

We generated $K = 50$ trials by adding the simulated noise to the simulated components, with an SNR of 1 (ratio of energy over periods of non-null simulated signal). Figure 1 presents an example of one trial for two electrodes.

E. Results

Figure 2 presents the spectra of the simulated noise, and of the sum (noise + signal). The fitted $1/f^\alpha$ function

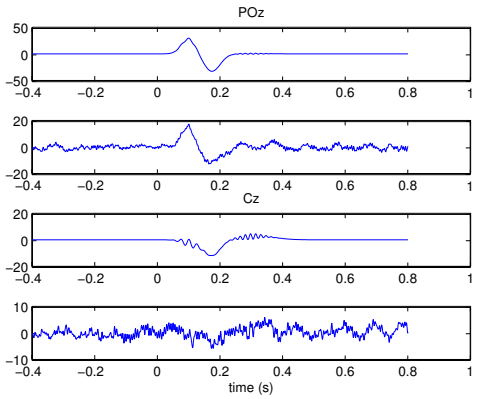

Fig. 1. Simulated signal and (signal + noise) combination, at two electrodes.

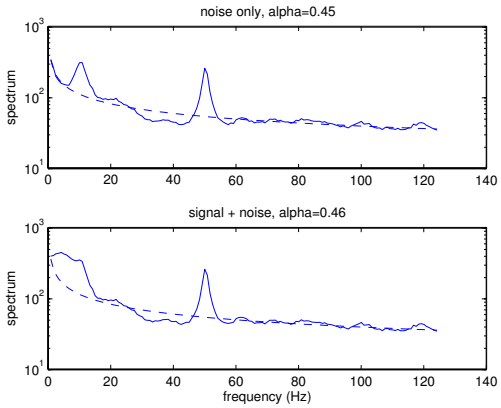

Fig. 2. Spectra of simulated noise (upper part) and (signal + noise) (lower part). Dashed lines: fitted $1/f^{\alpha}$ function.

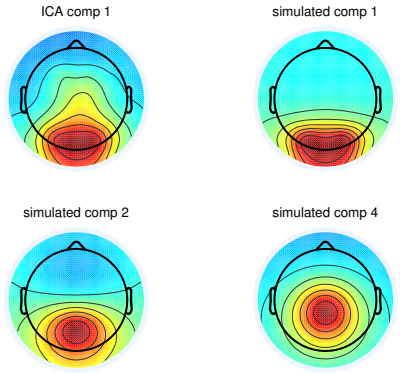

Fig. 3. Topographies of ICA1 and some simulated components.

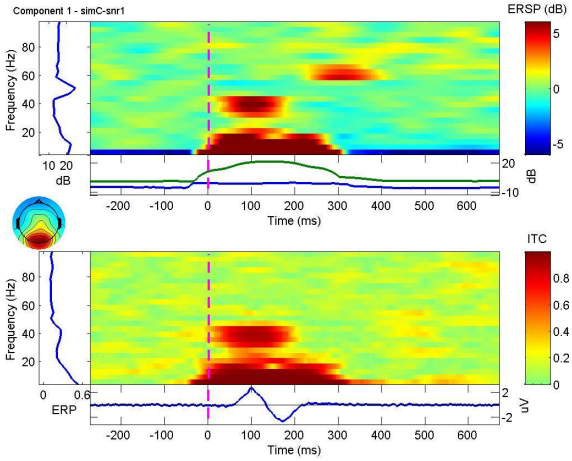

Fig. 4. Upper panel: event-related spectral power changes in the time-frequency plane, for ICA1. Lower panel: measure of phase locking. Below: average of ICA1 across trials

is similar in the two conditions, showing that the fit was scarcely influenced by the presence of signal components (the influence of the signal is visible in the low part of the spectrum, i.e. $< 10Hz$).

The topography of the first ICA component is shown in Figure 3. The occipital topography (simulated component 1, SC1) was recovered (the correlation coefficient between ICA1 and SC1 is 0.93). There was some contamination from the parietal activity (SC4), probably due to the correlation that was forced between these components. The separation with other components was successful.

The time frequency analysis of ICA component 1 (ICA1), presented in Figure 4, shows the evoked potentials and the early gamma (SC1). There is strong contamination (cross-talk) by the late gamma (SC2), possibly because of the spatial correlation between the patterns of SC1 and SC2.

The recursive search for time-frequency (TF) atoms is presented in Figure 5, on the time course (channels x trials) corresponding to the ICA component 1. In the first three TF planes, one can observe peaks that correspond to the evoked potentials, with latencies corresponding well to the ERP peaks (resp. 170 ms, 100 ms and 245 ms) . Atoms 4, 6 and 7 correspond to 50 Hz line noise, and atom 8 to 10 Hz activity (visible on the spectrum. Atom 5 could represent low-frequency residuals from the ERPs. Atom 9 corresponds to the early gamma activity, which frequency and latency (39.5 Hz and 100 ms) have been recovered properly.

The PARAFAC method on the mean data permitted to find clearly the topography of the occipital component SC1 (not shown), with a correlation coefficient of 0.85 between the PARAFAC topography and the SC1 topography. We were not able to find the high frequency simulated components, despite the prewhitening procedure.

F. Discussion

We have introduced a novel technique for identifying topography-time-frequency atoms in event-related M/EEG data. This method identifies components with a stable topography-time-frequency signature, by taking advantage of the correlation across channels and trials of a given component. This is complementary to the classical ICA procedure, which results in topographies and time courses independently of the trial-to-trial structure of the data.

The proposed frequency prewhitening preprocessing reveals high-frequency activity that was hidden in the data due

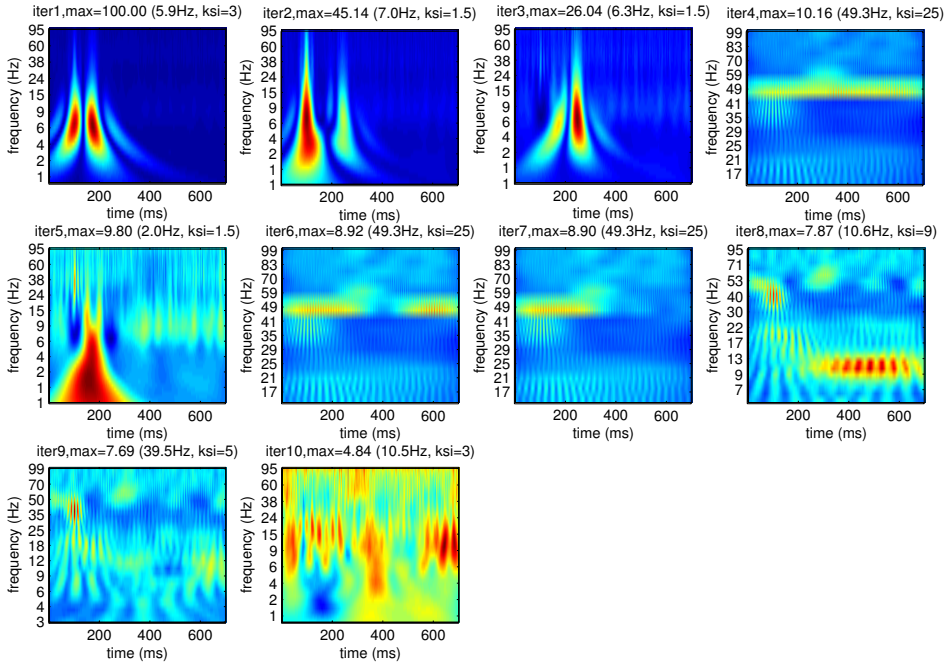

Fig. 5. Recursive search for time frequency atoms, on the time-course of first ICA component (ICA1). At each iteration, the average time-frequency transform is shown, corresponding to the shifting frequency ξ (number of oscillations) that had resulted in the higher correlation with the data.

to the $1/f^{\alpha}$ structure of M/EEG spectrum. It can therefore identify time-frequency atoms for both low-frequency (e.g., ERPs) and high-frequency activity (e.g., induced oscillations). Our procedure does not rely on a baseline, which allows to identify components not related to the protocol (50 Hz, alpha waves etc...). It can also identify activity of interest that is present in the baseline, as shown recently by Tallon-Baudry and colleagues on intra-cerebral data [12].

The topography-time-frequency decomposition can be used for better understanding the structure of a given M/EEG dataset. It can also be useful in analyzing single-trial data [13] by providing a parametrization of the events of interest [14], whether event-related potentials or oscillations.

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