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A comparison of methods for separation of transient and oscillatory signals in EEG

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ABSTRACT

Brain oscillations constitute a prominent feature of electroencephalography (EEG), in both physiological and pathological states. An efficient separation of oscillation from transient signals in EEG is important not only for detection of oscillations, but also for advanced signal processing such as source localization. A major difficulty lies in the fact that filtering transient phenomena can lead to spurious oscillatory activity. Therefore, in the presence of a mixture of transient and oscillatory events, it is not clear to which extent filtering methods are able to separate them efficiently.

The objective of this study was to evaluate methods for separating oscillations from transients. We compared three methods: finite impulse response (FIR) filtering, wavelet analysis with stationary wavelet transform (SWT), time–frequency sparse decomposition with Matching Pursuit (MP). We evaluated the quality of reconstruction and the results of automatic detection of oscillations intermingled with transients. The emphasis of our study was on epileptic signals and single channel processing.

In both simulations and on real data, FIR performed generally worse than the time–frequency methods. Both SWT and MP showed good results in separation and detection, each method having its advantages and its limitations. The SWT had good results in separation and detection of transients due to the time invariance property, but still did not completely resolve the frequency overlap for the oscillation during the time–frequency thresholding. The MP provides a sparse representation, and gave good results for simulated data. However, in the real data, we observed distortions introduced by the subtractive approach, and departure from dictionary waveforms. Future directions are proposed for overcoming these limitations.

1. Introduction

Electrophysiological brain signals recorded in EEG and MEG consist in a complex mixture of patterns reflecting activation of multiple neuronal networks. Some patterns are transient, i.e., sharp brain waves lasting only one or two cycles, while other consist in sustained oscillations. Examples of sharp transients are early evoked potentials in primary somatosensory regions recorded in intracerebral EEG (Krieg et al., 2010; Liegeois-Chauvel et al., 1991; Tallon-Baudry et al., 2005), or interictal spikes in epilepsy. Examples of physiological oscillatory patterns are theta, alpha and gamma rhythms. In epilepsy, cortical oscillations have been recorded in temporal lobe in the gamma band (Uchida et al., 2001; Hirai et al., 1999). At higher frequencies, epileptic ripples have been reported in intracerebral EEG (Bragin et al., 2002; Worrell et al., 2008) or in foramen ovale recordings (Clemens et al., 2007). Oscillation and transient may occur together, or in some cases can be directly linked though phase reset processes (Krieg et al., 2010).

The investigation of these patterns requires being able to characterize finely their spatio-temporal characteristics, which is not straightforward. In particular, a major difficulty lies in the fact that the frequency bands of transient and oscillatory activities may overlap. Indeed, it has been shown that filtering a transient with a classical bandpass filter leads to spurious oscillations or "false ripples" (Bénar et al., 2010). Therefore, in the presence of intermingled transient and oscillatory events, it is not clear to

Abbreviations: AUC, area under the curve (of the ROC); DWT, discrete wavelet transform; FIR, finite impulse response filter; FO, foramen ovale recording; MP, Matching Pursuit; MF, matched filter; MMP, multichannel Matching Pursuit; ROC, receiver operating characteristic; SWT, stationary wavelet transform.

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which extent filtering methods are able to separate efficiently these events.

An efficient separation is important for two aspects. The first aspect is the detection of oscillations, as a method sensitive to transients would induce false detections. The second aspect is the localization of the actual generators of oscillations with source localization methods without contamination by transients.

Several methods are available for the separation of activities in the frequency, time-scale or time–frequency domains (Mallat, 1989). These methods can be qualified by different aspects: linearity, adaptivity, and translation invariance.

The objective of this study was to quantify the capacities of different methods in separating oscillations from transients. We compared three methods: classical FIR filtering (linear, translation invariant), wavelet filtering with stationary wavelets (mixed approach), time–frequency sparse decomposition with Matching Pursuit (non linear, fully adaptive). We evaluated the quality of reconstruction of each event and the ability to detect oscillations intermingled with transients. Our emphasis was on single-channel processing.

In the first section, we describe the different separation methods, the simulated and real datasets. In the second section, we present the results obtained for both simulated and real data in terms of reconstruction accuracy, topography and localization results, and detection capacities. In the last section, we present conclusions and future directions.

2. Materials and methods

2.1. Signals

2.1.1. Simulations

The simulated datasets consisted in a mixture of transient signals (triangular waves) and oscillations with Gaussian envelope (Bénar et al., 2010). The parameters of the waves were in part inspired from our real signals. The time window was 300 ms, and the sampling frequency 1000 Hz. Across simulations, we varied several parameters: width of transient, frequency of the oscillation, relative amplitude of transient versus oscillation, signal to noise ratio. The range of parameters was inspired from our real signals. The triangle width was either 5 ms or 20 ms. The oscillation frequency was 10, 30, 45, 90 or 200 Hz. The width of the oscillation corresponded to a ξ of 8 (implemented as a fractional bandwith of 3 in the *gauspuls* Matlab function). The relative amplitude of the transient with respect to the oscillation was 1, 3, 5, 10 or 20. The time of occurrence of the transient was varied with equal steps across the time window of the oscillation, with five configurations. Background EEG activity was obtained from a neural mass model (Wendling et al., 2000) to ensure a physiologically plausible $1/f$ spectrum. The SNR, computed as $10 \times \log 10$ (signal energy/noise energy), was varied between -20 dB and 20 dB. A set of 25 noise realizations were generated for each SNR.

The construction of simulated signals and all signal processing were performed with the Matlab software (Mathworks, Natick, MA), with the help of the EEGLab toolbox (Delorme and Makeig, 2004).

2.1.2. Real signals

Real signals consisted in simultaneous foramen ovale (FO) and scalp EEG recordings. FO electrodes are invasive and record at the base of the brain (Zumsteg et al., 2005; Daskiewicz et al., 2009). FO electrodes permit to record epileptic fast activity from mesial and basal temporal brain structures, with high signal to noise ratio. Simultaneous recordings permit to test the capacities of methods for recovering non-invasively the oscillations.

These recordings were performed during presurgical assessment of a patient (female, 18 years old) with pharmacoresistant right medial temporal lobe epilepsy. Four hours of simultaneous FO and scalp EEG recordings were analyzed. Scalp recording consisted in 19 surface electrodes according to the 10–20 international system plus 4 temporo-basal electrodes (FT9, FT10, P9, and P10). All electrodes were referenced to FPz. Signals were recorded using BrainAmp amplifier system and BrainVision Recorder software (Brain Products Gmbh, Munich), with an online digital band-pass filter (0.15–200 Hz), digitized at a rate of 1 kHz. Epileptiform oscillations and transient were detected visually on the FO electrodes with help from an experienced electroencephalographer (M.G.).

2.2. Filtering methods

2.2.1. Finite impulse response filter (FIR)

The finite impulse response (FIR) filter is a linear, time-invariant method. The filter is defined by a difference equation:

$$f(t) = b_0 s(t) + b_1 s(t-1) + b_2 s(t-2) + \cdots b_N s(t-N) \tag{1}$$

where t is the sample number, $s(t)$ is the input signal, $f(t)$ is the output (filtered) signal, b_i, $i = \{1\ldots N\}$ are the filter coefficients, and N is the filter order. For off-line analysis, a simple way to find the coefficients is the Windowing Method. This consists of truncation of the sinc function with a temporal window, to obtain a finite impulse response (FIR) approximation of the ideal filter. In our case the Kaiser window was used because it provides minimal artificial oscillations (Bai et al., 2004; Cherif et al., 2008). The formulae provided by Kaiser (1974) permits to design the order N and shape parameter β of the Kaiser window that best approximate the desired passband and stopband frequencies (Fp and Fs, respectively) as well as the passband ripple and stopband attenuation (Rp and Rs, respectively) (matlab function kaiserord).

The passband ripple level was set to Rp = 3%, the attenuation Rs = 30 dB (depend on the passband ripple Rp). Two filters were designed, one bandpass for the oscillation and one bandstop for the transient, resulting in two impulse responses (*Kaiser* Matlab function) and filter parameters (*fir1* matlab function). Signals were filtered both forward and backward in order to eliminate latency shifts in the filtered signals (*filtfilt* Matlab function).

The bandpass frequencies were set to 8–11 Hz, 24–33 Hz, 35–50 Hz, 78–99 Hz, and 160–220 Hz.

2.2.2. Stationary wavelet transform (SWT)

A second option for separating oscillations and transient signals is wavelet (or time-scale) filtering by masking. The general principle of such filtering is to delineate the extent of the signal of interest in the time-scale plane (i.e., a binary mask) and to reconstruct only the selected coefficients. In this study, we use one particular type of invertible time–frequency transform, the stationary wavelet transform (SWT). The main advantage of SWT is its time-invariance property (Torrésani, 1995; Wang et al., 2003), in contrast with the discrete wavelet transform (DWT). The SWT has been shown to be useful in many applications like break down points detection and denoising (Dai et al., 2004). Generally, the redundancy of this transform facilitates the identification of salient features in a signal.

In the SWT, at each scale j and time step k the signal $s(t)$ is projected on the scaling function ϕ, dilated and translated:

$$cj, k = \left\langle s(t), \phi j, k(t) \right\rangle \tag{2}$$

$$\phi j, k(t) = 2^{-j} \phi(2^{-j}(t-k)) \tag{3}$$