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Adaptive tracking of EEG oscillations

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ABSTRACT

Neuronal oscillations are an important aspect of EEG recordings. These oscillations are supposed to be involved in several cognitive mechanisms. For instance, oscillatory activity is considered a key component for the top-down control of perception. However, measuring this activity and its influence requires precise extraction of frequency components. This processing is not straightforward. Particularly, difficulties with extracting oscillations arise due to their time-varying characteristics. Moreover, when phase information is needed, it is of the utmost importance to extract narrow-band signals. This paper presents a novel method using adaptive filters for tracking and extracting these time-varying oscillations. This scheme is designed to maximize the oscillatory behavior at the output of the adaptive filter. It is then capable of tracking an oscillation and describing its temporal evolution even during low amplitude time segments. Moreover, this method can be extended in order to track several oscillations simultaneously and to use multiple signals. These two extensions are particularly relevant in the framework of EEG data processing, where oscillations are active at the same time in different frequency bands and signals are recorded with multiple sensors. The presented tracking scheme is first tested with synthetic signals in order to highlight its capabilities. Then it is applied to data recorded during a visual shape discrimination experiment for assessing its usefulness during EEG processing and in detecting functionally relevant changes. This method is an interesting additional processing step for providing alternative information compared to classical time–frequency analyses and for improving the detection and analysis of cross-frequency couplings.

1. Introduction

Oscillatory phenomena have been the focus of increasing interest in neuroscience research. Neuronal oscillations have been proposed as a key mechanism for the large-scale integration of cognitive processes through which top-down internal states influence stimulus processing (Engel et al., 2001; Varela et al., 2001). Several models have been developed, with oscillations either serving as a binding mechanism bringing together different perceptions into a unified representation (Singer and Gray, 1995; Engel and Singer, 2001) or as a dynamic substrate for neuronal communication achieved through the coherence between brain areas (Fries, 2005). Also a more precise observation of specific oscillatory parameters can shed light on even more detailed brain processes. For instance, the ongoing oscillatory state of the brain before a given stimulus has been shown to provide valuable information about the subsequent behavioral responses in both motor and sensory tasks (Linkenkaer-Hansen et al., 2004; Womelsdorf et al., 2006). Additionally, the phase of neuronal oscillations was successfully linked to activity of single neurons (Jacobs et al., 2007). Finally, increasing evidence indicates that responses within classical neuronal frequency bands likely interact with each other through coupling mechanisms that remain to be identified (Jensen and Colgin, 2007). In this framework, cross-frequency couplings could provide a unifying mechanism for the intermingled neuronal oscillations acting at different temporal and spatial scales (Von Stein and Sarnthein, 2000), and recent studies tend to verify the existence, and the possible importance of cross-frequency couplings, during a variety of motor, sensory and cognitive tasks (Canolty et al., 2006; Lakatos et al., 2007; Demiralp et al., 2007).

Taken together, these findings raise the need for efficient methods for accurate estimation of oscillatory information such as phase, frequency and amplitude from raw signals. A well-known method widely used to get such spectral information is the Hilbert transform and its analytic signal representation (Gabor, 1946). However,

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although many studies have successfully identified and described phase synchronizations by applying this method to wide-band neuronal signals, it has been shown that proper estimation of oscillatory parameters can be performed only on narrow-band signals (Nho and Loughlin, 1999; Chavez et al., 2006). Moreover, subsequent synchronization measures such as the Phase Locking Value (Tass et al., 1998) are reliable only when applied to narrow-band signals (Celka, 2007). Therefore, band-pass filtering was applied to neuronal signals as a pre-processing step, in order to split the raw signals into narrow-band oscillations of different frequencies. Although this filter bank approach can lead to a more reliable analysis of oscillatory interactions (Canolty et al., 2006), a major drawback of such pre-processing should be mentioned. Because the cut-off frequencies of each band-pass filter must be pre-defined and remain constant during the whole analysis window, physiologically misleading outputs could be produced by the filters, in the case of a frequency component crossing the cut-off frequency limit of a filter. In such situations, it would be preferable to follow an oscillatory component in a continuous manner, without constraining the spectral content to fixed limits. This remark emphasizes the need for adaptive methods able to track narrow-band oscillations over time.

Recently, we proposed a novel method for adaptively tracking multiple oscillations in single-trial EEG signals (Uldry et al., 2009). In this article, we describe the tracking abilities of our algorithm for the estimation of single or multiple frequencies in both synthetic and EEG signals. The physiological relevance of well-known synchronization measures can be assessed using the temporal outputs of our method. Importantly, our previous publication on this tracking scheme is extended in order to clearly illustrate its capabilities for adaptive frequency estimation and its advantages over more traditional approaches for measuring cross-frequency couplings. In Section 2, we present the basics of our algorithm as well as its multi-frequency and multi-signal extensions, and we illustrate its performance on synthetic signals. In Section 3, we present the results of our method on real EEG single-trial signals in terms of adaptive frequency tracking, and demonstrate the benefit of applying common synchronization measures on the temporal outputs of our filters, compared to current methods.

2. Methods

The oscillation tracking methods are presented within the complex-valued signal framework. This approach simplifies several aspects of the computations. Especially, the filters are shorter (only one pole is needed for a complex band-pass filter, whereas two poles are required for a real band-pass filter). Of course, the signals of interest are real-valued in practice. But with the Hilbert transform one obtains the so-called analytic representation, whose real part is the original signal itself. Therefore, it is always possible to revert back to real-valued signals.

2.1. Frequency tracking

The frequency tracking algorithm presented in this paper is based on a real-valued scheme (Liao, 2005). It is composed of two parts; a time-varying band-pass filter and an adaptive mechanism that controls the central frequency of the filter. The structure is shown in Fig. 1. The input signal is defined as

$$x(n) = d(n) + w(n) = A(n)e^{j\omega(n)n} + w(n),$$

where $A(n)$ and $\omega(n)$ are the amplitude and the instantaneous frequency of the cisoid and $w(n)$ is an additive white complex centered noise. The output signal, $y(n)$, is obtained by filtering the input signal with a band-pass filter, with transfer function

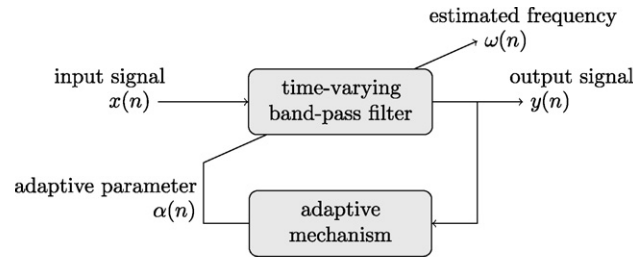

Fig. 1. Frequency tracking algorithm structure.

$$H(z, n) = \frac{1-\beta}{1-\beta\alpha(n)z^{-1}}. \tag{1}$$

The bandwidth is determined by β $(0 \ll \beta < 1)$ and $\alpha(n) = e^{j\omega(n)}$ is the adaptive parameter which controls the central frequency. This filter has unit gain and zero phase at $\omega(n)$.

The mechanism, which tracks the oscillations and updates the filter, is based on the complex discrete oscillator equation

$$d(n) = e^{j\omega_0}d(n-1) = \alpha_0 d(n-1). \tag{2}$$

This equation is satisfied for a cisoid at frequency ω_0. Therefore given $d(n)$ and $d(n-1)$, it is possible to obtain the frequency with

$$\omega_0 = \mathrm{Arg}\{\alpha_0\}, \quad \alpha_0 = \frac{d(n)}{d(n-1)}.$$

In a time-varying and noisy scenario, the coefficient $\alpha(n+1)$ can be estimated by minimizing the mean square error (MSE) of the oscillator equation (2) for the output signal, $y(n)$, of the adaptive filter (1):

$$J(n) = \mathrm{E}\{|y(n) - \alpha(n+1)y(n-1)|^2\}. \tag{3}$$

Setting $\partial J(n)/\partial\alpha(n+1) = 0$, the optimal solution is

$$\alpha(n+1) = \frac{\mathrm{E}\{y(n)\bar{y}(n-1)\}}{\mathrm{E}\{|y(n-1)|^2\}}$$

where the upper bar denotes the complex conjugate. However, this expression is not applicable in practice. Therefore, the expectations are replaced by exponentially weighted averages (Haykin, 2001), and the adaptive mechanism becomes

$$\alpha(n+1) = \frac{Q(n)}{P(n)} = \frac{\delta Q(n-1) + [1-\delta]y(n)\bar{y}(n-1)}{\delta P(n-1) + [1-\delta]|y(n-1)|^2} \tag{4}$$

where δ $(0 \ll \delta < 1)$ controls the convergence rate. The modulus of coefficient $\alpha(n+1)$ is then brought back to unity to ensure the stability of the band-pass filter. Finally, the frequency estimate is obtained with $\omega(n+1) = \mathrm{Arg}\{\alpha(n+1)\}$.

2.2. Multiple frequency tracking

Typically, multiple oscillatory components are active at the same time in EEG signals. The method described previously can be extended to the multi-component case. Now, it is assumed that the input signal is composed of K cisoids with additive complex noise, i.e.

$$x(n) = \sum_{k=1}^{K} d_k(n) + w(n) = \sum_{k=1}^{K} A_k(n)e^{j\omega_k(n)n} + w(n)$$

where $A_k(n)$ and $\omega_k(n)$ are the amplitude and the instantaneous frequency of the kth cisoid and $w(n)$ is an additive white complex centered noise. The basic idea of the extension is to use one frequency tracking algorithm from Section 2.1 to track each component. However, because the band-pass filters (1) are not ideal