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A wavelet-based method for local phase extraction from a multi-frequency oscillatory signal

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Abstract

One of the challenges in analyzing neuronal activity is to correlate discrete signal, such as action potentials with a signal having a continuous waveform such as oscillating local field potentials (LFPs). Studies in several systems have shown that some aspects of information coding involve characteristics that intertwine both signals. An action potential is a fast transitory phenomenon that occurs at high frequencies whereas a LFP is a low frequency phenomenon. The study of correlations between these signals requires a good estimation of both instantaneous phase and instantaneous frequency. To extract the instantaneous phase, common techniques rely on the Hilbert transform performed on a filtered signal, which discards temporal information. Therefore, time–frequency methods are best fitted for non-stationary signals, since they preserve both time and frequency information. We propose a new algorithmic procedure that uses wavelet transform and ridge extraction for signals that contain one or more oscillatory frequencies and whose oscillatory frequencies may shift as a function of time. This procedure provides estimates of phase, frequency and temporal features. It can be automated, produces manageable amounts of data and allows human supervision. Because of such advantages, this method is particularly suitable for analyzing synchronization between LFPs and unitary events.

Keywords: Rat; Olfaction; Wavelet transform; Ridge extraction; Oscillation phase

1. Introduction

For about 10 years, the study of local field potentials (LFPs) has received an increasing interest, particularly because such signals appear to be relevant indicators of information processing. LFPs, which are considered as the summation of excitatory and inhibitory dendritic potentials (Mitzdorf, 1987), are often oscillatory. Oscillatory synchrony of LFPs between different cortical areas probably has a true functional role. Indeed, it has been shown in human intra-cranial recordings that the holding of visual information in short-term memory is accompanied by oscillatory synchrony in the β band (15–20 Hz) across distinct visual areas (Tallon-Baudry et al., 2001). In a similar experiment in monkeys, two sites located over the posterior infero-temporal cortex are synchronized in the β band during a memory maintenance task in correct trials, while the synchrony fails to develop in incorrect trials (Tallon-Baudry et al., 2004). On the other hand, as LFP oscillations are supposed to originate in the rhythmical synchronization of groups of neurons (Mitzdorf, 1987), several teams have studied the temporal relationship existing between oscillations and neuronal spike discharges. It has thus, been reported that both activities can become phase-locked under certain behavioral or perceptual conditions (Murthy and Fetz, 1996; Fries et al., 2001; Siegel and König, 2003). Hence, when studying the coherence between LFP oscillations from different brain regions, or the synchronization between spikes and LFP oscillations, the quantification of oscillation phase becomes crucial and the results will depend on its accuracy.

Abbreviations: LFP, local field potential; CWT, continuous wavelet transform; WFT, windowed Fourier transform; LTRS, low time-resolution scalogram; HTRS, high time-resolution scalogram; SPIPH, spike preferential instantaneous phase histogram; SNR, signal to noise ratio

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The traditional Hilbert transform method for phase extraction can only be applied after the signal has been Fourier-filtered around the frequency band of interest if the signal contains oscillations at different frequencies. Although this method is very efficient, it has a major drawback as it suppresses all temporal information. Indeed, the Fourier representation describes the signal as a sum of infinite oscillations and mixes time and frequency information. For non-stationary signal studies, many time–frequency methods exist that analyze the local frequency composition of the signal while preserving temporal information (see Boashash, 1992a,b for review). Among these methods, parametric methods require the operator to have an insight into the data: specifically, the operator needs to determine the frequency range of the oscillatory phenomenon and/or the time boundaries of the oscillatory epochs. Conversely, non-parametric methods such as time–frequency representations (Flandrin, 1993) offer a convenient setup, in which the problem of local amplitude estimation is well understood and addressed, but only in the case of single component signals (Boashash, 1992a,b; Delprat et al., 1992). Further refinements of this setup, described by Carmona et al. (1997), can be used to address multi-component or noisy signal (Carmona et al., 1999). However, an important issue is the computational cost of such methods. The time–frequency map computation multiplies the original amount of data several folds, which could rapidly saturate the computational capabilities of any computer, rendering any further processing or human visual check virtually impossible. This is particularly true in a situation where a high sampling rate leads to a huge number of samples and where, for each sample, precise phase and frequency information is to be extracted.

Here, we propose a new algorithmic procedure, based on wavelet ridge extraction (Delprat et al., 1992), to extract instantaneous frequency and instantaneous phase information from signals sampled at high rate. This method is very robust even when multiple oscillatory regimes are simultaneously present. Moreover, it produces a computationally manageable amount of data. Consequently, it is well suited for the study of synchronization between spike activity and LFP oscillations in the olfactory system of the freely breathing rat, where LFPs oscillate in at least two frequency bands, β and γ, both regimes alternating within each respiratory cycle (Buonviso et al., 2003).

2. Methods

2.1. Continuous wavelet transform and wavelet ridge

2.1.1. Continuous wavelet transform

In order to preserve time and frequency information, one commonly uses time–frequency representation based on a windowed Fourier transform (WFT) or a continuous wavelet transform (CWT). We chose to use CWT instead of WFT because the window size depends on the screened frequency, in case of CWT, as opposed to WFT fixed window size. This represents an asset of the method since the duration of oscillations often shortens as the frequency increases. CWT provides a better compromise between time and frequency resolution. The CWT yields a series of coefficients in time representing the evolution of the frequency content (Mallat, 1998) of the signal x by:

$$T_{\Psi}[x](t,a) = \int x(s)\Psi^*_{t,a}(s)\,\mathrm{d}s \quad a>0, t\in R$$

where t stands for time, a for the scale and * for the complex conjugate. The functions $\Psi_{t,a}$ are obtained by dilation and translation of a unique waveform $\Psi:\Psi(t,a)=(1/\sqrt{a})\Psi((s-t)/a)$. The function Ψ, called mother wavelet, is a function with mean value equal to zero, and is characterized by its center frequency (f_0), its spread in time $\sigma_t=\int|\Psi(s)|^2\,\mathrm{d}s$ and its spread in frequency $\sigma_f=\int|\hat{\Psi}(\omega)|^2\,\mathrm{d}\omega$ (where $\hat{\Psi}$ indicates the Fourier transform). By decreasing or increasing a, the basis function $\Psi_{t,a}$ is fitted to a segment of $x(t)$; hence, a indirectly represents the frequency of the signal. Squaring the results and dividing by the scale $P_x(t,a)=|T_x(t,a)|^2/a$ generates a time–scale energy density distribution called normalized scalogram. $P_x(t, a)$ represents the energy of the signal in a time–frequency box whose center and size are defined by (t, (f_0/a)) and ($a\sigma_t$, (σ_f/a)), respectively: when $f(=(f_0/a))$ increases (a decreases), the time resolution improves and the frequency resolution worsens. Different families of mother wavelets can be applied. The choice is influenced by the nature of the information to be extracted. For the determination of instantaneous frequency, the most commonly used wavelet is the so-called Morlet wavelet (Kronland-Martinet et al., 1987), defined in the time domain by $\Psi(t)=(1/2\pi)\,\mathrm{e}^{-i2\pi f_0 t}\mathrm{e}^{-t^2/2}$ and in the frequency domain by $\hat{\Psi}(f)=(1/2\pi)\,\mathrm{e}^{-2\pi^2(f-f_0)^2}$. A wavelet family is characterized by the constant $\omega_0=2\pi f_0$. For large ω_0, frequency resolution improves at the expense of time resolution. To obtain a wavelet with mean value equal to zero, we need to set $\omega_0>5$ (Grossman et al., 1989).

2.1.2. Wavelet ridge extraction

The method determining instantaneous frequency from wavelet ridges was first proposed by Delprat et al. (1992) where the phase coherence of the wavelet transform was used to obtain a numerical estimate of the ridge. For noisy, and/or multi-component signals, Carmona et al. (1997, 1999) proposed to use the localization of the scalogram maxima instead. Note that the detection algorithm is only a particular post-processing method of a time–frequency transform. It can thus, be used with other time–frequency energy representations such as WFT or more generally the family of smoothed Wigner distributions (Auger and Flandrin, 1995; Carmona et al., 1999).

Considering a sinusoidal signal given by the complex exponential function: $x(t)=\mathrm{e}^{-i2\pi f_T t}$ where f_T denotes the frequency, the wavelet transform of the signal is: $T_{\Psi}[x](t,a)=\sqrt{a}\hat{\Psi}(af_T)\,\mathrm{e}^{-i2\pi f_T t}$

Substituting the Fourier transform of the Morlet wavelet into this equation, we obtain for the normalized scalogram $P_x(a,b)=(1/4\pi^2)\,\mathrm{e}^{-2\pi^2(af_T-f_0)^2}$. Deriving this scalogram with respect to a, we obtain $(\delta P_x/\delta a)(a,b)=f_T(af_T-f_0)\,\mathrm{e}^{-2\pi^2(af_T-f_0)^2}$. In such conditions, the point (t, a_R) where $\delta P_x/\delta a=0$ verifies $a_R f_T-f_0=0$ and corresponds to the maximum energy of the scalogram. The scalogram is then essentially maximum in the neighborhood of a curve $a_R(t)$, which is the