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Comparison of spectral analysis methods for characterizing brain oscillations

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Abstract

Spectral analysis methods are now routinely used in electrophysiological studies of human and animal cognition. Although a wide variety of spectral methods has been used, the ways in which these methods differ are not generally understood. Here we use simulation methods to characterize the similarities and differences between three spectral analysis methods: wavelets, multitapers and $P_{episode}$. $P_{episode}$ is a novel method that quantifies the fraction of time that oscillations exceed amplitude and duration thresholds. We show that wavelets and $P_{episode}$ used side-by-side helps to disentangle length and amplitude of a signal. $P_{episode}$ is especially sensitive to fluctuations around its thresholds, puts frequencies on a more equal footing, and is sensitive to long but low-amplitude signals. In contrast, multitaper methods are less sensitive to weak signals, but are very frequency-specific. If frequency specificity is not essential, then wavelets and $P_{episode}$ are recommended.

Keywords: Oscillations; EEG; Wavelets; Multitapers; $P_{episode}$

1. Introduction

Oscillations arise from an interaction between the intrinsic properties of neurons (excitability) and their interconnectivity, giving rise to synchronous activity (Buzsáki and Draguhn, 2004). Oscillations at various frequencies may be readily seen in electroencephalographic (EEG) recordings across species and are known to correlate with an animal's behavior and with the stimulating conditions present in the environment. Although early studies relied on visual inspection of the EEG signal to identify epochs of oscillatory activity and their behavioral correlates (Berger, 1929), the advent of modern computers now enables researchers to quantify the presence of oscillatory components in the EEG using spectral analysis methods. Spectral methods are widely used throughout the neurosciences and have yielded many new findings concerning the electrophysiology of both animal and human cognition (e.g., Klimesch et al., 1994; Kahana et al., 2001; Bastiaansen and Hagoort, 2003; Buzsáki and Draguhn, 2004; Kahana, 2006).

A myriad of spectral methods exist, which differ in the aspects of the data they highlight. However, exactly what aspects are highlighted by each method is often unclear. Our goal in this paper is to compare three methods used in the analysis of EEG oscillations. All three methods involve Fourier analysis. That is, they all seek to decompose the time series of EEG activity into sinusoidal functions whose amplitude and phase vary across frequency, but the shape of these functions differ for each method. In a traditional Fourier analysis, the function with which the signal is convolved[1] is a sinusoid of fixed length, and in order to improve temporal specificity, the analysis is performed on short windows ("windowing"). However, traditional Fourier analysis has a number of shortcomings: it has relatively poor time–frequency resolution (Bruns, 2004), the length of the window fixes the scale of the to-be-detected signal, and it is mainly designed for stationary[2] and regular signals (Mallat, 1998; Zhan et al., 2006). Because of the fixed window length, Fourier analysis is only useful in a limited frequency range that is optimized

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[1] A convolution measures the overlap between two functions by shifting them over one another and integrating over all shifts.

[2] 'Stationary' means that the signal has no significant change in its mean over time.

for your time window (Perrier et al., 1995). Moreover, none of the conventional oscillatory analysis methods differentiate oscillations from artifacts and evoked potentials, which can manifest as short events in Fourier space. Therefore, several alternatives have been proposed for analyzing brain oscillations, some of which will be discussed here.

We will examine three methods, namely wavelets (introduced for neural data in Kemerait and Childers (1972) and Schiff et al. (1994)), multitapers (introduced for the analysis of neural data in Mitra and Pesaran (1999)) and P_{episode} (introduced in Caplan et al. (2001)). Wavelets are functions that can come in many shapes, and the analyzed signal is decomposed into scaled and shifted versions of the oscillating waveform you are using. Because the wavelet functions are shifted and scaled versions of one another, the proportion between temporal width and frequency bandwidth remains the same for all frequencies. Therefore, a crucial difference from windowed Fourier analysis is that the size of the window depends on the frequency, which gives rise to more temporal precision for higher frequencies. Wavelets have a very good time–frequency resolution trade-off (Sinkkonen et al., 1995), making them quite useful for the analysis of non-stationary signals.

Multitapers are sets of functions that were designed to reduce bleeding between frequencies, rendering them well-suited for non-stationary processes with high dynamic ranges and/or rapid variations (Walden et al., 1998). An important distinction from wavelets is that the width of the function stays the same in absolute time across frequencies (similar to a Fourier transform). Finally, because *multi*tapers imply that the signal is convolved with multiple orthogonal tapers,[3] which are then averaged, the variance of this oscillation detection method across repeated measurements is reduced. In other words, the amplitude measurements taken with multitapers will have smaller error bars than, for example, wavelets.

Both wavelets and multitapers do not discriminate between short, high-amplitude power fluctuations and longer oscillations. The P_{episode} method addresses this issue because it was designed to detect “oscillatory episodes” and ignore transient voltage fluctuations (Caplan et al., 2001). This method characterizes whether oscillations at a given frequency are present or absent at a given time point in an ongoing EEG signal. It uses wavelets to determine the amplitude of oscillatory activity at a given frequency and time, and then applies an amplitude and duration threshold to characterize whether the signal is in an oscillatory state. Instead of measuring mean oscillatory power, Caplan et al.’s method measures the fraction of a time interval during which the signal exceeds the amplitude and duration threshold at a given frequency. This fraction is then termed the probability of being in an oscillatory episode at frequency f, or $P_{\text{episode}}(f)$. It is likely that the number of oscillatory cycles is more relevant than absolute length for information processing and computation (for an example see Jensen, 2006; Ward, 2003). Therefore, we will perform most analyses in this paper in units of oscillatory cycles at a given frequency as opposed to time in seconds, an alternative way of quantifying oscillatory power.

We will compare these methods by first analyzing simulated EEG data where the signal to be recovered is known. We then apply the three methods to empirical data. Comparing the results from simulations to effects in real data will allow us to highlight the differences between the three methods. We end the paper by offering recommendations to scientists interested in measuring oscillatory effects in EEG data.

2. Methods

2.1. Specifications of analysis methods

The first method we consider is wavelet analysis (Fig. 1a and d). Wavelets come in many shapes, each designed to capture different aspects of a time series. The Morlet wavelet is commonly used for the analysis of human EEG (Schiff et al., 1994) because its sinusoidal shape, which tapers at the ends, matches the signal we expect to extract from the EEG. This is crucial, because the success of wavelet analysis depends upon the suitability of the wavelet for detecting the desired signal (Özdemir et al., 2005). A small disadvantage of the wavelet is that it is non-orthogonal, hence computationally inefficient.[4] The Morlet wavelet is defined as follows (illustrated in Fig. 1g):

$$S^W = s(t) * \frac{1}{(\sigma_t\sqrt{\pi})^{1/2}}\, \mathrm{e}^{-(t^2/2\sigma_t^2)}\, \mathrm{e}^{2i\pi\, ft} \quad (1)$$

In this equation, S^W denotes the wavelet-transformed signal, $s(t)$ is the original signal, t and f represent time and frequency, respectively, and $*$ means convolution. The square root term causes the wavelet to be normalized to have an energy (squared integral) of 1. After the convolution, the absolute magnitude of the square of Eq. (1) will be taken. Wavelets have a length that scales inversely with frequency, such that the time–frequency product, or alternatively the number of cycles of oscillations within a wavelet, remains constant (the actual number of oscillations is set by the wavenumber k in $\sigma_t = k/\pi f$). It also means, however, that for higher frequencies the frequency resolution decreases and the temporal resolution increases (i.e., temporal and frequency resolution trade-off). In this paper, we use a wavenumber of 6, which is often used in human EEG analysis to strike a balance between temporal and frequency specificity (e.g., Sederberg et al., 2003, in press). In addition, the decomposition we use is a continuous wavelet transform, which has the advantage that we can investigate signals at arbitrary scales (as opposed to a decomposition at a fixed set of orthogonal frequencies–the discrete wavelet transform). However, it has the disadvantage that the wavelets used are not necessarily orthogonal (as is the case when the frequencies used are not logarithmically spaced) and, hence, the obtained power estimates are

[3] Tapers are functions that smooth the data by having a value of one in the middle and then slowly tapering off to zero at the edges.

[4] Non-orthogonal refers to overlap or correlation between the different wavelets, which essentially means that the overlapping part is convolved with your data twice. This is what is meant by ‘computationally inefficient’.