Empirical Mode Decomposition: A Method for Analyzing Neural Data

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Abstract

Almost all processes that are quantified in neurobiology are stochastic and nonstationary. Conventional methods that characterize these processes to provide a meaningful and precise description of complex neurobiological phenomenon may be insufficient. Here, we report on the use of the data-driven Empirical Mode Decomposition (EMD) method to study neuronal activity in visual cortical area V4 of macaque monkeys performing a visual spatial attention task. We found that Local Field Potentials were resolved by the EMD into the sum of a set of intrinsic components with different degrees of oscillatory content. High-frequency components were identified as gamma band (35-90 Hz) oscillations, whereas low-frequency components in single-trial recordings contributed to the average visual evoked potential (AVEP). Comparison with Fourier analysis showed that EMD may offer better temporal and frequency resolution. The EMD, coupled with instantaneous frequency analysis, may prove to be a vital technique for the analysis of neural data.

Keywords: Selective visual attention; Empirical mode decomposition; Gamma synchronization; Hilbert transform; Nonstationary.

1. Introduction

In neurobiology, one often has to deal with time series data that are nonstationary. Fourier-based methods are only designed for the frequency analysis of stationary time series, and thus have limited use in revealing the underlying neurophysiological variations in such data. The major drawback of Fourier-based approaches is that the basis functions are fixed, and therefore cannot capture any time-varying characteristics of neural signals.

In the present analysis, we use a new method, called Empirical Mode Decomposition (EMD), that was first introduced by Huang et al. (1998a). The decomposition is based on direct extraction of the signal energy associated with various intrinsic time scales. The technique adaptively decomposes nonstationary signals into a set of intrinsic oscillatory modes. The components, called Intrinsic Mode Functions (IMFs), allow the calculation of a meaningful multi-component instantaneous frequency by virtue of the Hilbert transform. Thus one can potentially localize events in time and

frequency. Here, we explore the use of EMD to study neuronal activity in visual cortical area V4 of macaque monkeys performing a visual spatial attention task [1].

Local Field Potentials (LFPs) and multiunit activity were simultaneously recorded from multiple V4 sites with overlapping receptive fields (RFs). The monkey fixated a central spot, and after a short delay, two stimuli were presented at equal eccentricity, one inside and one outside the RFs. On separate trials, the monkey was required to attend to the stimulus at one (target) location, and was rewarded for responding when the target changed color, ignoring changes at the other (distracter) location. Target and distracter color changes were equiprobable and distributed uniformly between 0.5-5 sec after stimulus onset. The result was two attention conditions: attention inside the RF vs. attention outside the RF. The analysis described here used LFPs from one V4 site on 300 trials correctly performed by a monkey whose attention was directed within the RF of that site.

In the sections below, we begin with a brief introduction to the EMD method, then describe the results of its application to V4 LFP data, and finally discuss the neurophysiological processes that it suggests.

2. Methods

Huang's data-driven EMD method was initially proposed for the study of ocean waves [2], and found immediate applications in biomedical engineering [3, 4]. The major advantage of EMD is that the basis functions are derived directly from the signal itself. Hence the analysis is adaptive, in contrast to Fourier analysis, where the basis functions are fixed sine and cosine waves.

The central idea of this method is an iterative sifting process that decomposes a given signal into a sum of Intrinsic Mode Functions (IMFs), those basic building blocks that make up data complex time series. A signal must satisfy two criteria to be an IMF: (1) the number of extrema and the number of zero crossings are either equal or differ at most by one; and (2) the mean of its upper and lower envelopes equals zero. The first criterion is similar to the narrow-band requirement. The second criterion modifies a global requirement to a local one, and is necessary to ensure that the instantaneous frequency will not have unwanted fluctuations as induced by asymmetric waveforms. To make use of EMD, the signal must have at least two extrema – one maximum and one minimum to be successfully decomposed into IMFs.

Given these two definitive requirements of an IMF, the sifting process for extracting an IMF from a given signal $x(t)$ is described as follows:

1. Two smooth splines are constructed connecting all the maxima and minima of $x(t)$ to get its upper envelope, $x_{\text{up}}(t)$, and its lower envelope, $x_{\text{low}}(t)$; The extrema can be simply found by determining the change of sign of the derivative of the signal. Once the extrema are identified, all the maxima are connected by a cubic spline line as the upper envelope. The procedure is repeated for the local minima to produce the lower envelope. All the data points should be covered by the upper and lower envelopes.
2. The mean of the two envelopes is subtracted from the data to get their difference $d(t) = x(t) - (x_{\text{up}}(t) + x_{low}(t))/2$.

3. The process is repeated for $d(t)$ until the resulting signal, $c_1(t)$, the first IMF, satisfies the criteria of an intrinsic mode function.

The residue $r_1(t) = x(t) - c_1(t)$ is then treated as new data subject to the sifting process as described above, yielding the second IMF from $r_1(t)$. The procedure continues until either the recovered IMF or the residual data are too small, in the sense that the integrals of their absolute values or the residual data have no turning points. Once all of the wavelike IMFs are subtracted from the data, the final residual component represents the overall trend of the data.

At the end of this process, the signal $x(t)$can be expressed as follows:

$$x(t) = \sum_{j=1}^{N} c_j(t) + r_N(t)$$

where N is the number of IMFs, $r_N(t)$ denotes the final residue (signal trend), and $c_j(t)$ are nearly orthogonal to each other, and all have zero means. Due to this iterative procedure, none of the sifted IMFs is derived in closed analytical form.

In practice, after a certain number of iterations, the resulting signals do not carry significant physical information, because, if sifting is carried on to an extreme, it could result in a pure frequency modulated signal of constant amplitude. To avoid this, we can stop the sifting process by limiting the standard deviation, computed from two consecutive sifting results, which is usually set between 0.2 and 0.3. By construction, the number of extrema is decreased when going from one residual to the next, and the whole decomposition is guaranteed to be completed with a finite number of modes.

By the sifting process, the data are represented by intrinsic mode functions, to which the Hilbert transform can be applied. The Hilbert spectrum enables us to represent the amplitude and the instantaneous frequency as functions of time in a three-dimensional plot. The resulting time-frequency distribution of the amplitude is called the Hilbert amplitude spectrum. The two-step procedure, EMD and its subsequent Hilbert spectral analysis, is called the Hilbert-Huang Transform (HHT) [2]. The HHT method provides not only a more precise definition of particular events in time-frequency space than wavelet analysis, but also more physically meaningful interpretations of the underlying dynamic processes.

3. Results

Fig.1 shows two single-trial LFP recordings (having different lengths) from area V4 in the macaque, their IMFs, and the instantaneous frequencies of IMF components. Although there is variation from trial to trial in the number of components produced by EMD, two general features are quite similar for individual trials: (1) strong gamma-band oscillations are observed to dominate the highest frequency (C1) component; and (2) the instantaneous frequencies reveal clear frequency variation of each component as a function of time, reflecting the fact that the data are not stationary.

The Hilbert transform of all IMF components gives a Hilbert spectrum. Fig.2 (right) shows such a Hilbert energy spectrum averaged across all the trials for attention inside the receptive field. As a comparison, the short-time Fourier transform (spectrogram) [5] of the same data is shown in Fig.2

(left). Both the Hilbert spectrum and the spectrogram show general agreement about the concentration of gamma-band energy in time and frequency. However, the Hilbert spectrum gives a sharper and more refined definition of the energy contour, whereas the spectrogram spreads energy over a much wider frequency range. It is evident from Fig. 2 (right) that the Hilbert spectrum clearly depicts fluctuations of the gamma frequencies (40~70 Hz) over time.

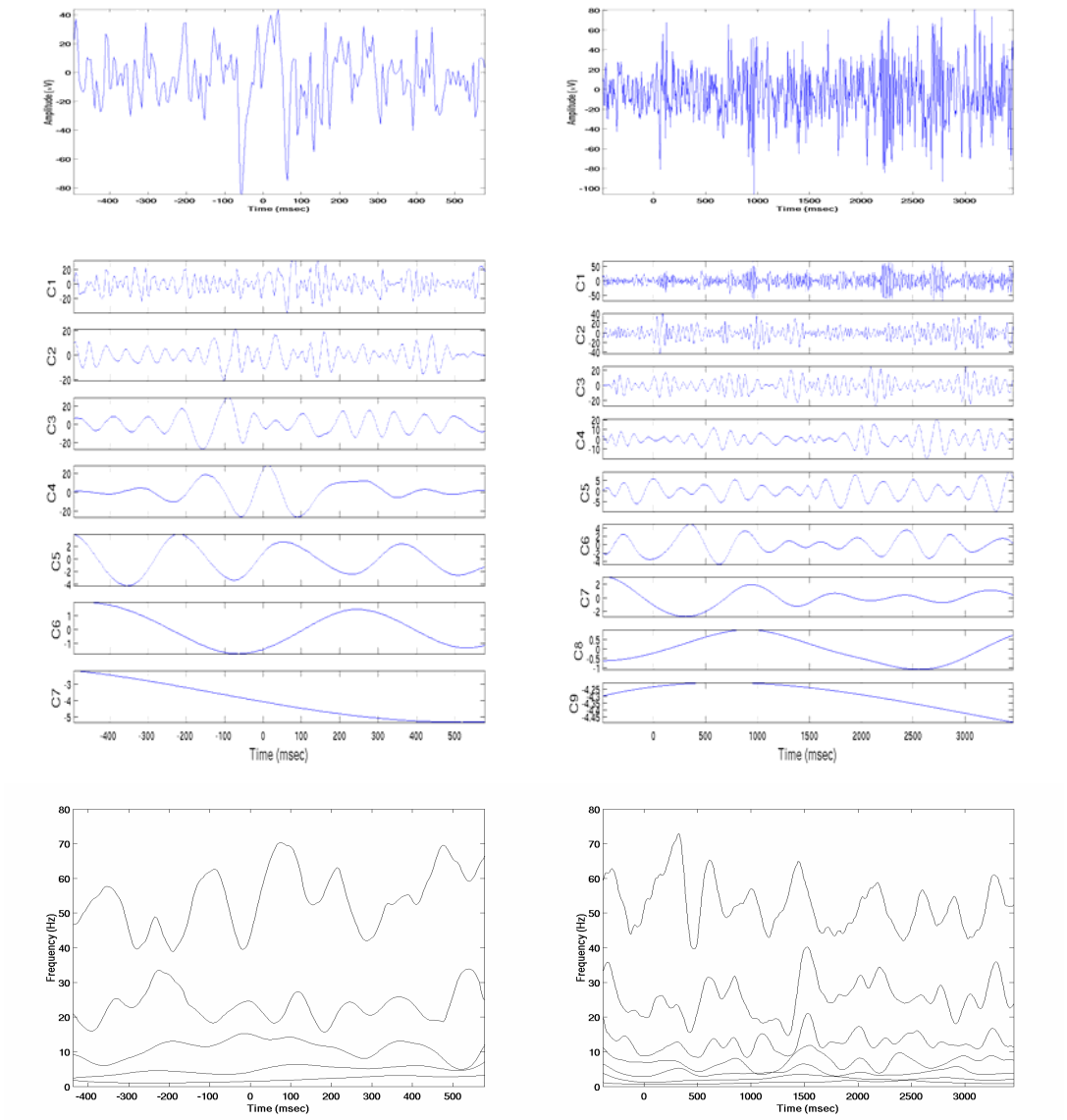

Fig.1. Two typical trials of LFP recordings (**top**) with different lengths, intrinsic mode functions (IMFs, **middle**) and their smoothed instantaneous frequencies as functions of time (**bottom**). **Left** shows the result from a short recording having seven IMFs, and **right** from a long recording having nine IMFs. Time 0 indicates the stimulus onset. Note that both trials show the C1 components in the gamma frequency range. The large variation of instantaneous frequencies of IMF components indicates that the data are not stationary. The highest-numbered components (lowest frequency) are equivalent to the trends in the data, suggesting that another benefit of EMD may be trend removal.

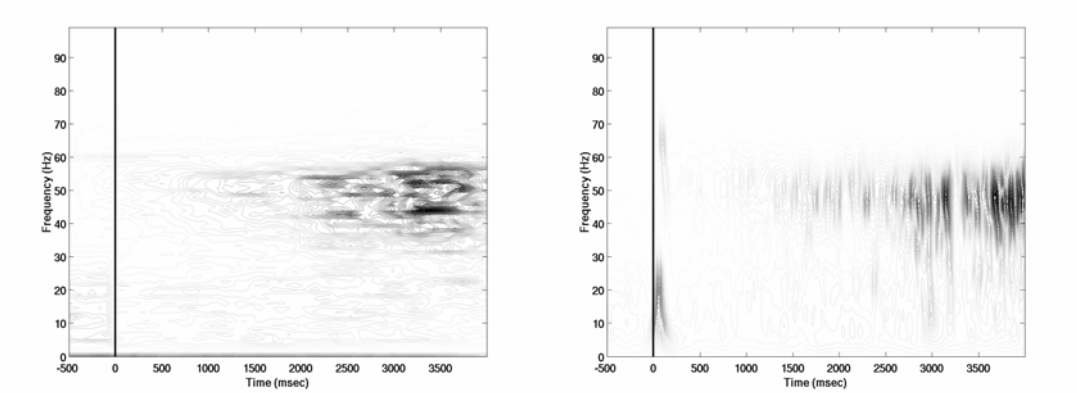

Fig.2. Comparison between the short-time Fourier spectrum (spectrogram) and the Hilbert spectrum. **Left:** The short-time Fourier spectrum for V4 recording site 1 for attention inside the receptive field. **Right:** The ensemble averaged Hilbert spectrum of the same data, where the spectrum is smoothed by a 21 x 21 Gaussian filter. We see that there is a wider energy smearing in the frequency space in the short-time Fourier spectrum, which fails to give the detailed gamma frequency variations.

By averaging the low-frequency components (the last three components) over single trials, we obtain the average visual evoked potential (AVEP), as shown in Fig.3 at long (left) and short (right) time scales. Computing the AVEP by the EMD (Fig.3, dark lines) offers a striking contrast to that obtained by directly averaging the single-trial data (Fig.3, gray lines). The difference between these two approaches becomes less pronounced as more trials are averaged. By verifying that a realistic average can be computed from single-trial EMD components, it is suggested that the analysis of these single-trial components may also prove useful in some applications.

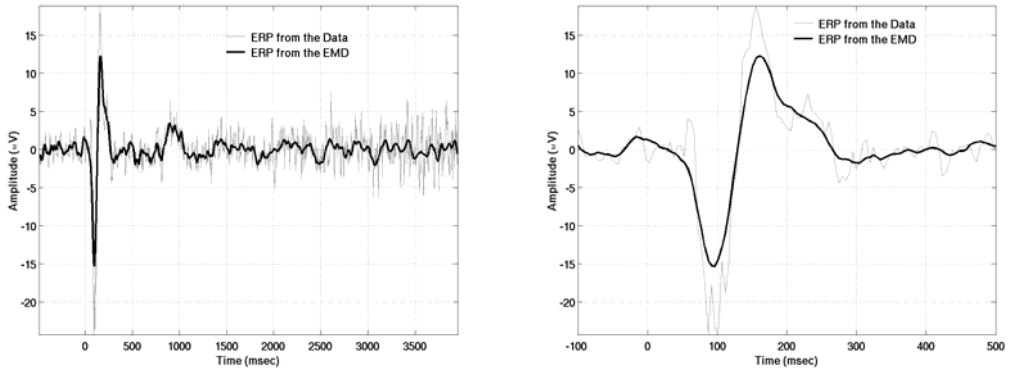

Fig.3. Average visual evoked potentials (AVEPs, left) and their expansions from 100 ms prestimulus to 500 ms poststimulus (right) obtained from the EMD method (dark line) by selecting the low-frequency IMFs and that obtained directly from data by direct ensemble averaging (gray line). We see that there is a close match between these two approaches. The single-trial low-frequency components that went into the average might also prove useful for applications requiring single-trial analysis.

4. Discussion and Conclusions

In this paper, we have presented a novel method for the analysis of neurobiological time series using Empirical Mode Decomposition (EMD). We have shown that, by using EMD, LFPs from cortical area V4 are resolved into the sum of a set of intrinsic components having different degrees of oscillatory content. The high-frequency components are identified as gamma band (35-90 Hz) oscillations, whereas the low-frequency components are the major contributions to AVEP. The

EMD, coupled with instantaneous frequency analysis, may prove to be a vital technique for the analysis of neural data.

The decomposition technique is based on the local characteristic time scale of the data, whose basis functions (or IMFs) used to represent the given signal are nonlinear functions that are directly extracted from the data. Therefore, the time scale is defined by the data per se, rather than by a pre-determined value. Fourier analysis cannot separate these IMFs without using pre-assigned cut-off frequencies. This is the crucial difference between EMD and Fourier-based filtering. Comparison with Fourier analysis has shown that EMD offers much better temporal and frequency resolution.

In applying EMD to local field potentials in the spatial attention task, we have found that gamma-band activity is mostly concentrated in the highest frequency component (C1). We have also observed in some trials that the gamma activity is not exclusively found in the C1 component due to the trial-to-trial variability. This observation underscores the need for all of the relevant IMF components to be interpreted together if the data being investigated do not possess a clear, physically meaningful separation of scales.

To summarize, we have introduced here a new method for analyzing local field potential data. The EMD offers an alternative and advantages over Fourier-based methods. We feel that that this new technique deserves to be further tested for its utility in the field of neural data analysis.

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References

[1] P. Fries, J.H. Reynolds, A.E. Rorie, R. Desimone, Modulation of oscillatory neuronal synchronization by selective visual attention, *Science*, 291 (2001) 1560-1563.

[2] N.E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N-C. Yen, C. C. Tung, H. H. Liu, The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis. *Proc. Royal Soc. Lond. A* 454 (1998a) 903-995.

[3] W. Huang, Z. Shen, N.E. Huang, and Y.C. Fung, Engineering analysis of biological variables: An example of blood pressure over 1 day. *Proc. Nat. Acad. Sci. USA*, 95 (1998b) 4816-4821.

[4] H. Liang, Z. Lin, R.W. McCallum, Artifact Reduction in electrogastrogram Based on the Empirical Model Decomposition Method, *Medical & Biological Engineering & Computing*, 38 (2000) 35-41.

[5] A. V. Oppenheim and R. W. Schafer, *Digital Signal Processin*g; Prentice Hall: Englewood Cliffs, NJ, 1989.