# Empirical Mode Decomposition: A Method for Analyzing Neural Data

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**Abstract**

Almost all measurements in neurobiology are stochastic and nonstationary. Conventional methods to use these measurements to provide a meaningful and precise description of complex neurobiological phenomenon are insufficient. Here, we report on the use of Huang's data-driven Empirical Mode Decomposition (EMD) method (Huang et al. 1998a) to study neuronal activity in visual cortical area V4 of macaque monkeys performing a visual spatial attention task (Fries et al. 2001). 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). We also discovered that the magnitude of time-varying gamma activity was enhanced when monkeys attended to a visual stimulus as compared to when they were not attending to the same stimulus. These results support the idea that the magnitude of gamma activity reflects the modulation of V4 neurons by visual spatial attention. 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 oscillatory, stochastic, and nonstationary. Most traditional methods, including Fourier analysis and wavelet analysis, are insufficient to reveal the underlying physiological variations in such data. The major drawback of these approaches is that the basis functions are fixed, and do not necessarily capture the time-varying nature of 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 we can localize any event on the time as well as the frequency axis. 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 (Fries et al. 2001).

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 monkeys' attention was directed to the stimulus at one (target) location, and they were 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 300 correctly performed trials in each attention condition from one monkey.

In the sections below, we begin with a brief introduction to the EMD method, then describe the results of its use, and finally discuss the physiological responses that it suggests.

## 2. Methods

Huang's data-driven EMD method was initially proposed for the study of ocean waves (Huang et al., 1998a), and found immediate applications in biomedical engineering (Huang et al., 1998b; Liang et al. 1999). 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 linear combinations of fixed sine and cosine waves.

The central idea of this method is the sifting process to decompose a given signal into a sum of Intrinsic Mode Functions (IMFs), those basic building blocks that make up complicated data. 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 IMFs 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. Repeat the procedure 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 satisfies the criteria of an intrinsic mode function.

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 Hilbert transform can be used. 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. As such, the 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 LFP recordings from area V4, their IMFs, and the instantaneous frequencies of IMF components for two typical trials with different lengths. 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 in single trials, dominated by the highest frequency (C1) component; and (2) there is clear frequency variation of each component as a function of time revealed by its instantaneous frequency, reflecting the fact that the data are not stationary.

The Hilbert transform of all IMF components gives a Hilbert spectrum. Fig.2 (left) shows such a Hilbert spectrum averaged across all the trials for attention inside the receptive field. It is evident from Fig. 2 (left) that the broad gamma-band activity between 40 Hz and 70 Hz changes as a function of time. A similar Hilbert spectrum is observed for attention outside the RF condition, but with a lower magnitude of gamma activity. The

difference between conditions can clearly be seen by comparing how the mean magnitudes of the highest-frequency (C1) component for the two conditions change as a function of time (Fig. 2, right).

By averaging the low-frequency components over single trials, we obtained the average visual evoked potential (AVEP), as shown in Fig.3 (red). Computing the AVEP by the EMD offers a striking match with that directly obtained from the data (Fig.3, blue). 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.

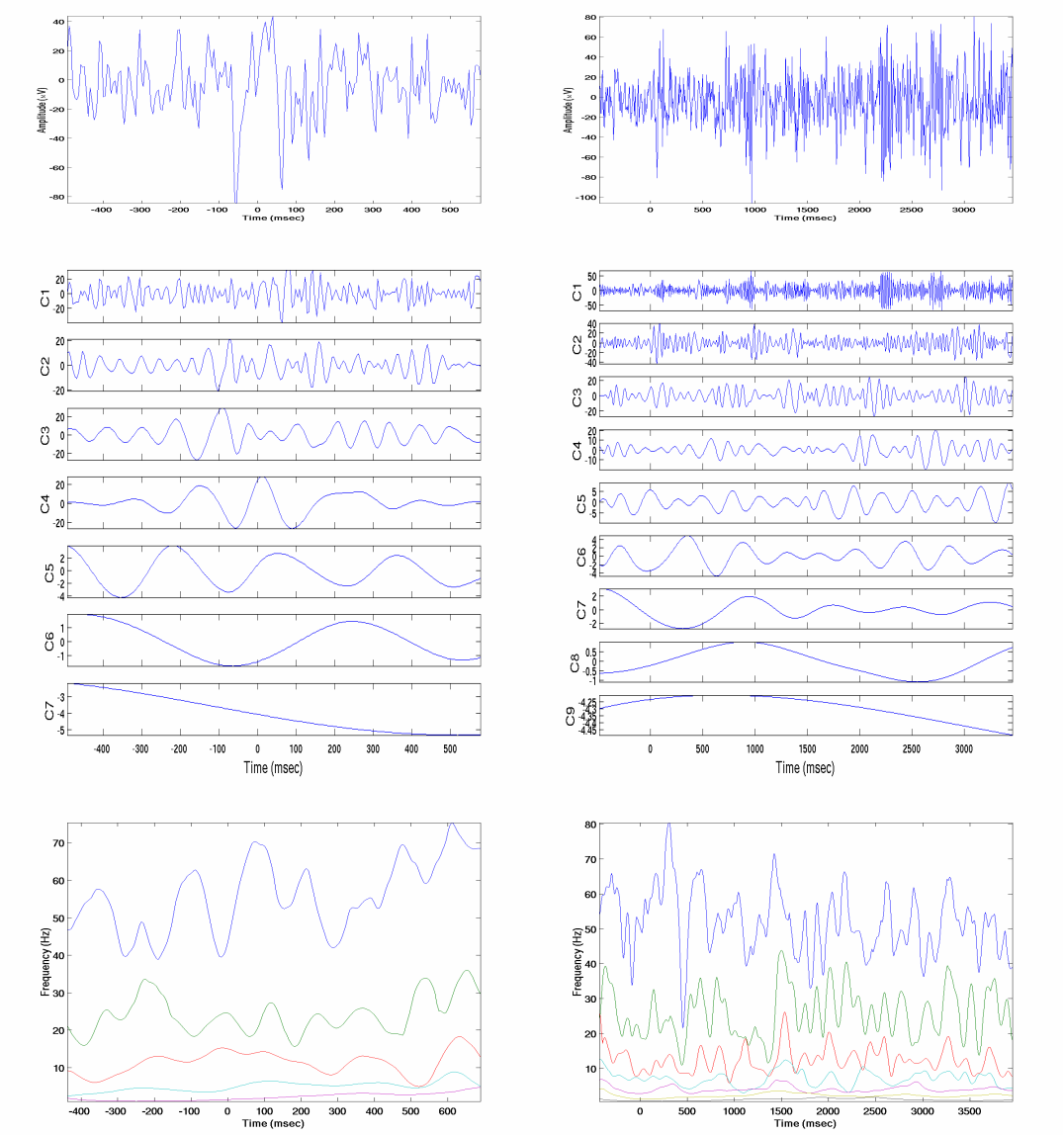


Fig.1. Two typical trials of LFP recordings (**top**) with different lengths, intrinsic mode functions (IMFs, **middle**) and their instantaneous frequencies as functions of time (**bottom**). **Left** shows the result from a short recording having seven IMFs, and **right** from a long recording having nine IMFs. Time 0 indicates the stimulus onset. Note that both trials show gamma frequency components, dominated by the C1

components. 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.

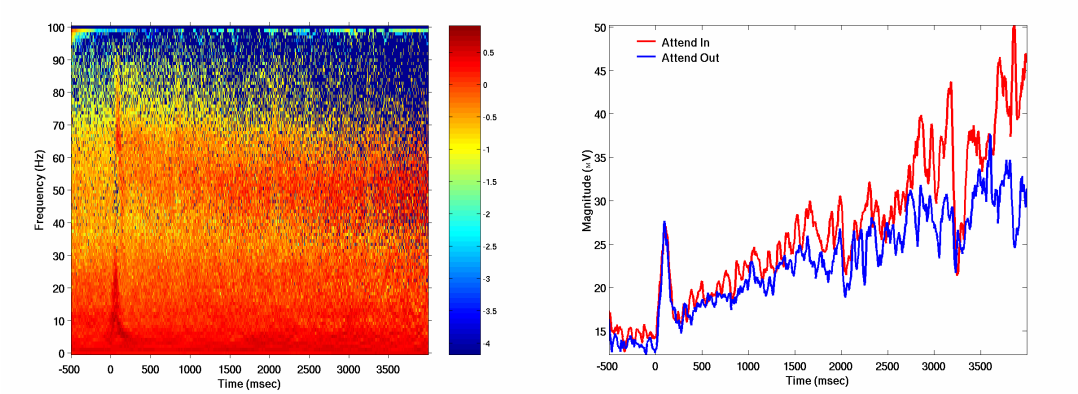


Fig.2. The ensemble averaged Hilbert spectrum for V4 recording site 1 for attention inside the receptive field (**left**) and the mean magnitudes of the gamma frequency components as functions of time for two condition (**right**), attention inside the receptive field (red) and attention outside the receptive field (blue). Note that both conditions show similar temporal profiles, but that the gamma activity is larger for attention inside the receptive field.

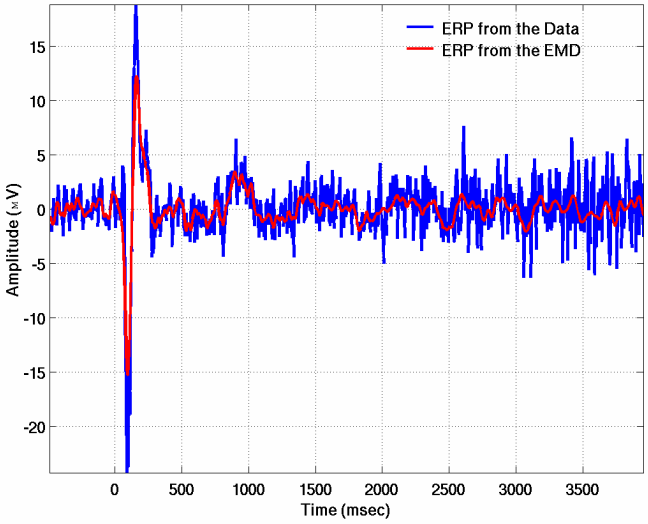


Fig.3. Average visual evoked potentials (AVEPs) obtained from the EMD method (red) by selecting the low-frequency IMFs and that obtained directly from data by the simple ensemble average (blue). We see that there is a close match between these two approaches. The single-trial low-frequency components that went into the average might also prove for applications requiring single-trial analysis.

## 4. Conclusions

In this brief report we presented a novel method for the analysis of neurobiological time series using EMD. We showed that, with the EMD, LFPs from cortical area V4 were resolved into the sum of a set of intrinsic components with different degrees of oscillatory content. The high-frequency components were identified as gamma band (35-90 Hz)

oscillations, whereas the low-frequency components in the single recordings were the contributions to AVEP. We also showed that the time-varying gamma activity magnitude was enhanced when monkeys attended to a visual stimulus as compared to when they were not attending to the same stimulus. These results support the idea that the magnitude of gamma activity reflects the modulation of V4 neurons by visual spatial attention (Desimone & Duncan 1995). The EMD, coupled with instantaneous frequency analysis, may prove to be a vital technique for the analysis of neural data.

The results obtained so far are highly encouraging. Yet, the robustness of the method on large databases remains to be evaluated. Currently, the analysis is being streamlined to automatically identify and extract gamma components from single trials, and is being expanded to systematically assess attention-modulated gamma synchronization for all the recording sites for all sessions of several monkeys.

## Acknowledgements

Supported by NIMH-IRP, NIMH and NSF.

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