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Estimation of Instantaneous Power in the EEG to Assess Brain Connectivity with High Temporal Resolution

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Abstract—**This paper presents advanced signal processing algorithms to quantify brain connectivity with high temporal resolution using the electroencephalogram (EEG). The experimental paradigm exploits the visual cortex response to flickering images at a given frequency. The envelope of the EEG at the flickering frequency collected by 128 electrodes over the head quantifies the communication amongst the brain areas with high temporal resolution. This work proposes to use the empirical mode decomposition to find the flickering frequency and then use the Hilbert transform to estimate the instantaneous amplitude. A video of the topographical display of the instantaneous power over the array helps us visualize the exquisite communication that occurs during the stimulus presentation.**

I. INTRODUCTION

BRAIN activity and its relation to behavior and cognition have been important research topics for many decades. In recent years, functional Magnetic Resonance Imaging (fMRI) has been a primary methodology to quantify brain activity in cognitive studies because of its very high spatial resolution. However, its temporal resolution is constrained by the speed of blood flow. For example, any neural activity in a given brain region is measured with ~1 sec time constant, where the signatures of cognition exist at a time scale of 30-100 msecs. Therefore, we can not track these activities only thru fMRI, especially to analyze brain connectivity. The electroencephalogram (EEG) has a higher temporal resolution, so it looks like a better tool to analyze brain connectivity even though its spatial resolution is worse and the signal to noise ratio (SNR) of the cognitive response is generally negative.

In order to address the poor SNR this paper explores a different paradigm that has been recently developed [1]. Subjects are presented imagery that flickers at a known frequency. It is well known that the flickering of an image produces in the visual cortex a rhythmic component at the flicker frequency [2]. What is less known is that the amplitude of the flickering frequency is modulated over the head depending upon the attentive state of the subject and also on the affective content of the image [1]. We can possibly quantify the communication among the different brain areas by estimating the instantaneous power of the flickering activity. The advantage is that the SNR is rather high for flicker frequencies above 10 Hz, which enables *single trial analysis*.

The signal processing methodologies to quantify instantaneous power are rather different from the conventional algorithms used in EEG analysis and they are the objective of this paper. In order to preserve the property of high temporal resolution, instantaneous quantities such as instantaneous power, are required to represent the changes of the brain over time. Here, we suggest the empirical mode decomposition (also called the Hilbert-Huang transform [3]) as the preprocessor since it finds with high accuracy periodic components in the EEG. After this step, the instantaneous amplitude of the flickering frequency is obtained by the Hilbert transform and squared to obtain the estimate of the instantaneous power with a temporal resolution given by the sampling frequency. A movie of the instantaneous power over the electrode array shows the evolution of the communication between the visual cortex and the rest of the brain areas. In section II, Hilbert-Huang method is explained with some examples of the data, and in section III we present some explanation about the filter and show the result when applying Hilbert-Huang transform and the filter on the EEG signal. Finally, the conclusion is present in section IV.

II. METHODS

As is well known, a signal can be either analyzed in the time domain to quantify time structure or equivalently its Fourier transform will display which frequency components exist in the signal. However, very often we are interested in estimating changes in signal frequency composition across time with high temporal resolution. In such cases, the Hilbert transform [4] [5] is our primary tool to go beyond the intrinsic definition of frequency over a window embedded in Fourier analysis. Basically, with the Hilbert transform, we are converting the given real time series into a complex time series, which shows an instantaneous amplitude or frequency over time. Furthermore, if we square the instantaneous amplitude, instantaneous power will be estimated, and it is the quantity we propose to use in our investigation of cortical connectivity in response to the external visual stimulus.

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A. Hilbert Transform

Hilbert transform (HT) can be explained either in the frequency or time domains, which also means that we have two families of algorithms to perform the Hilbert transform. In the frequency domain the basic HT operation is to shift the phase of positive and negative frequency components of the signal by -90° and +90°, respectively, and then to compute an inverse Fourier transform of the phase shifted version to get the corresponding time domain signal, i.e.

$$\hat{G}(f) = -j\,\mathrm{sgn}(f)G(f) \tag{1}$$

$$\hat{g}(t) = F^{-1}\left[\hat{G}(f)\right] \tag{2}$$

where, $G(f)$ is Fourier transform of $g(t)$, $\hat{G}(f)$ is a phase shifted version of $G(f)$, sgn represents the sign function, and $\hat{g}(t)$ is the corresponding Hilbert transformed time signal.

Note that Hilbert transform has no effect on the amplitude of the signal because it only changes the phase of the spectral components of the signal. This frequency domain based Hilbert transform, which uses in practice the FFT and IFFT algorithms is the one utilized here [5].

The Hilbert transform can be also performed in the time domain because we can simply inverse Fourier transform the phase shift operation (3), and then convolve it with the original signal.

$$F^{-1}[-j\,\mathrm{sgn}(f)] = \frac{1}{\pi t} \tag{3}$$

$$\hat{g}(t) = \frac{1}{\pi t} * g(t) \tag{4}$$

B. Analytic Signal

Given signal, $g(t)$, the analytic signal, $g_+(t)$, can be constructed using the HT signal, $\hat{g}(t)$, in the following way,

$$g_+(t) = g(t) + j\hat{g}(t) = |g_+(t)|e^{\arg[g_+(t)]} \tag{5}$$

This formulation allows us to access to the instantaneous quantities, i.e the instantaneous amplitude or phase, from which thru differentiation we obtain the instantaneous frequency. Its corresponding frequency domain expression is also found in (6).

$$G_+(f) = G(f) + j[-j\,\mathrm{sgn}(f)G(f)] = 2u(f)G(f) \tag{6}$$

where, $G_+(f)$ is a Fourier transform of the analytic signal, and $u(f)$ represents unit step function in frequency domain. As seen from (6), the frequency components of the analytic signal only appear in positive frequency region.

However, there is a practical problem with the method that is related to the phase wrapping intrinsically related to the principal argument used in the arg function in (5). If the original signal is not narrow band, recovering the original phase is very difficult and artifacts occur often in the instantaneous amplitude and frequency. Figure 1 shows a segment of the occipital EEG when the subject is seeing the flickering picture (f=17.5 Hz) and the corresponding instantaneous frequency, which shows some artifacts.

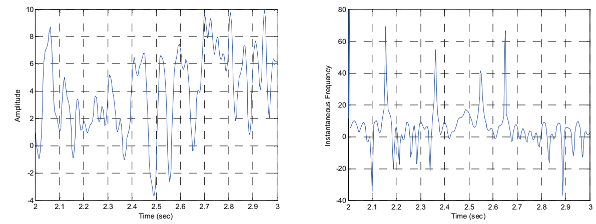

Fig. 1. Electroencephalogram (EEG) Signal and Instantaneous Frequency

To mitigate this problem, we propose here the use of the Empirical Mode Decomposition proposed by Huang [3]. The appeal of this decomposition is that it decomposes the signal into its own modes instead of projecting them in fixed basis such as exponentials or wavelets. Since we are looking for the amplitude of the flickering frequency, EMD seems to be very appropriate.

C. Hilbert-Huang Transform

Huang suggested the empirical mode decomposition method [3] as a preprocessor for the Hilbert transform to deal with the unwrapping problem. First, the decomposition method assumes that the signal is deterministic and stationary. The advantage is that the procedure uses the signal as its own decomposition and a recursive procedure to extract a sequence of components starting from the highest frequency until the slowest frequency of interest [3]. Each mode can be found by the process, called sifting, and the step by step procedure applied to $x = 5\sin(2\pi f_1 t) + \sin(2\pi f_2 t) + \sin(2\pi f_3 t)$ where, f_1=3 Hz, f_2=10 Hz, and f_3=20 Hz is shown in Table I and the empirical modes are also shown in Figure 2. As observed from the result, the decomposition method successfully extracted each frequency component of the original signal at each mode.

TABLE I
EMPIRICAL DECOMPOSITION PROCESURE (SIFTING)

a.	Find local maxima and minima of the signal
b.	Connect local maxima and minima by cubic spline, respectively
c.	Draw a mean function between two splines
d.	Subtract the mean function from the original signal
e.	Consider the resulting signal as the original signal and repeat (a-e) until the criterion is satisfied
f.	If the criterion is satisfied, the resulting signal is determined as the mode
g.	Subtract the mode from the original signal and repeat (a-g) for another mode selection
h.	Stop process if the remaining signal is monotonically increasing or decreasing

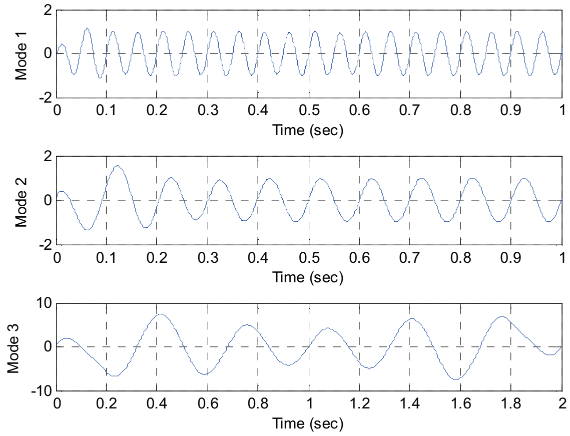

Fig. 2. First (20Hz), Second (10Hz), and Third (3Hz) Modes

The stopping criterion of the process for our case is a mixture of two criteria, which uses the mean square difference and number of zero-crossing and extrema at the same time. Specifically, mean square difference is set to 0.00001, and S-number is set to 1.

III. EEG Signal

For the analysis, EEG signals were collected from 128-channel HydroCell with a lowpass filter whose cutoff frequency is 42Hz, and the sample rate was 250 Hz. Now, we are all set to extract the instantaneous power from the EEG signal. Given an original EEG signal, Figure 4a, of channel 74 (for the location, refer to Figure 3), where the subject is stimulated by a 17.5 Hz flicking human face picture and the stimulus starts at 300ms, we can decompose it into several modes using the empirical decomposition method. The first three modes are shown in Figure 4b. The instantaneous amplitude of each mode is also plotted in Figure 4b (Red). As can be seen from the graph, the EMD decomposed the EEG into simpler oscillating modes. Since we are interested in the f =17.5 Hz component, we suggest to take the FFT of each mode and stop the decomposition when a large peak of 17.5 Hz in the FFT is found. In our data set the flickering frequency is normally found in the first mode, Figure 4c.

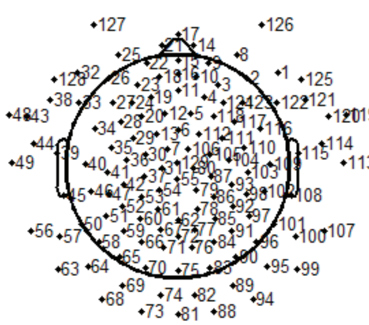

Fig. 3. Channel Configuration (128 Channel HydroCel GSN)

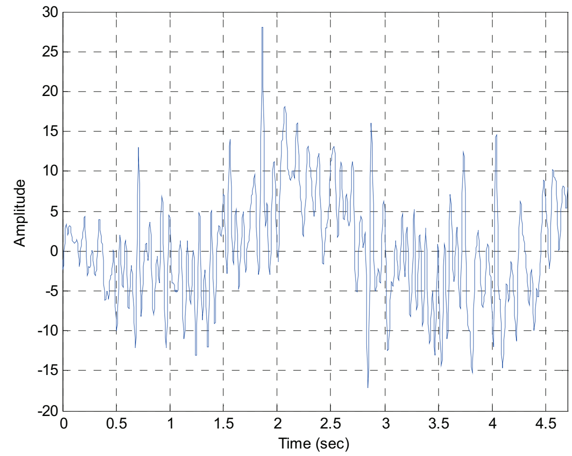

Fig.4. (a) Original signal (channel 74)

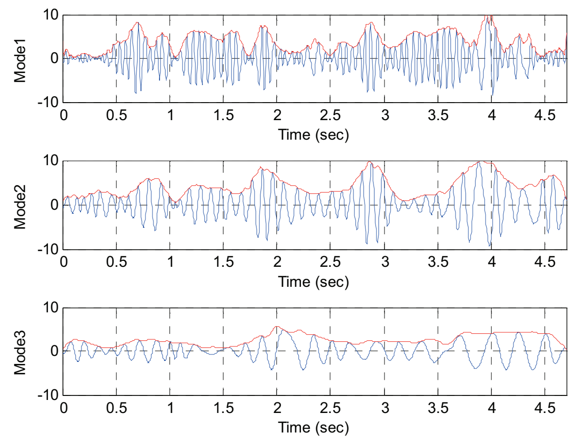

Fig.4. (b) Each Mode and its Instantaneous Amplitude

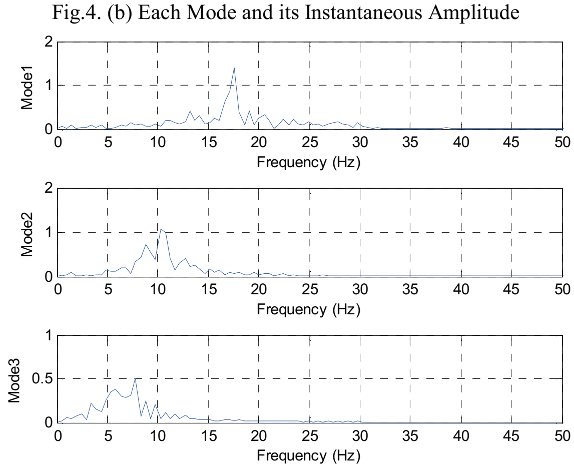

Fig.4. (c) Fourier Transform of Each Mode

However, examining closely the EMD first mode, we know that we can only say that on average its main frequency component is 17.5 Hz, because the visual cortex has its own dynamics, and the instantaneous frequency changes around the stimulus frequency. Moreover, it is unknown if the other cortices will always display this same frequency because they may not be communicating with the visual cortex. Therefore, we need to further process the resulting EMD to remove other frequency components. To achieve this, we apply the following method. We check every half period of the signal in time domain, and then remove the half periods greater than 15 Hz or less than 21 Hz. In order to avoid an abrupt on/off rule, we still maintain the out of band half periods if they are isolated (i.e. if there are 3 half waves in band in the last 5 half periods, we keep all of them). The Hilbert transform is then computed and the instantaneous amplitude squared to obtain the instantaneous power. The estimated instantaneous power at the flickering frequency of the EEG of Figure 4 is shown in Figure 5 (Blue). For comparison with another method, a plain passband FIR filter with cutoff frequency [15 21] Hz is applied to the same data to extract the flickering signal, instead of EMD, and its estimated instantaneous power is also drawn in Figure 5 (Red). The overall shape of two plots is similar, but the filtered version is delayed, smoother and misses important activity (around 1 and 4 sec) and distorts the amplitudes. These differences stem from the ability of EMD, to preserve local periodicities of the original signal irrespective of the frequency, while the passband filter smoothes them. However, the large peak at 4 sec may be an artifact, which shows the issues of the EMD approach.

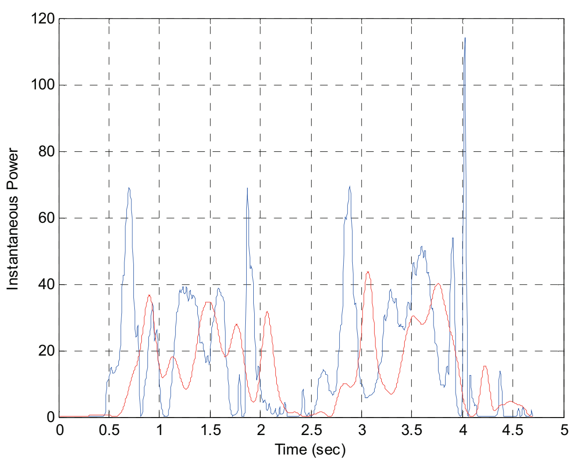

Fig.5. Instantaneous Power by HHT (Blue) and Passband Filter (Red)

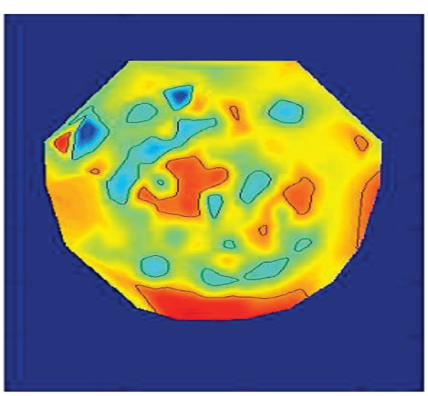

Fig.6. Interpolated Brain Image at 800ms

We applied the same Hilbert-Huang method and the period filter to all 128 EEG channels to extract the instantaneous power of every channel mode where a prominent f=17.5 Hz signal appears, and mapped them into a color coded topographic map as shown in Fig 6 at 800 msec after stimulus. The instantaneous power is normalized into the range of 0 to 255, and the image was plotted using 2D interpolation method, which uses triangle-based cubic interpolation. Each map is constructed at the sampling frequency resolution (4 msec). A video is constructed for all images and it helps psychologists visualize how the stimulus is propagated over the cortical areas.

IV. CONCLUSION

The methodology presented in this paper is a first step to quantify the changes in instantaneous EEG power over the cortex using a flickering stimulus. The advantage of the flickering stimulus is that it allows for single trial cognitive experimentation with a high SNR. This may enable real time cognitive feedback to the subject. The signal processing methodology is very different from the ones normally used in EEG analysis, and we exploited here the combination of the empirical model decomposition and Hilbert transform. Even though this methodology is sensitive to noise and it also suffers from the stationarity assumption, when used with caution seems to preserve the amplitude of the envelope at the flickering frequency. But much more work is necessary to establish the robustness of the method. There are some alternative signal processing methodologies that should be also compared to the one described here. Moreover, one needs to automatically extract the information from the videos and start quantifying dependence and causality of the communication between brain areas.

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