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Empirical Mode Decomposition Improves Detection of SSVEP

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***Abstract*—Steady State Visual Evoked Potentials (SSVEPs) have been used to quantify attention-related neural activity to visual targets. This study investigates how empirical mode decomposition (EMD) can improve detection accuracy and rate of SSVEPs. First, the scalp-recorded electroencephalogram (EEG) signals are decomposed into intrinsic mode functions (IMFs) by EMD. Then, IMF components accounting for SSVEPs are selected for target frequency detection. Finally, target frequency is identified by two methods: Gabor transform and Canonical Correlation Analysis (CCA). This study quantitatively explores the impact of EMD on the target frequency detection. Empirical results show that the EMD improves their recognition accuracy when Gabor transform is used, even in a shorter Gaussian window, but has little effects on the performance of the CCA. Further, this study finds that harmonic responses of the target frequency can be used to enhance the SSVEP detection both for the Gabor transform and CCA.**

I. INTRODUCTION

Brain-Computer Interface (BCI) allows users to control special computer applications using brain activity. Most of BCI approaches are based on Electroencephalography (EEG) recorded from the scalp. Steady-state visual evoked potentials (SSVEPs) are natural brain responses to repetitive visual stimuli, such as a flicker on a computer screen. The frequency range associated with the SSVEPs normally comprises the fundamental frequency of the visual stimulus as well as its harmonics [1-3].The SSVEP-based BCI capitalizes these fast and natural brain responses to detect where a user visually fixates/attends. Many related works [4-11] have received widespread attention in recent decades.

Time-frequency analysis and Canonical Correlation Analysis (CCA) are two classical methods used in detecting the frequencies of SSVEPs [12-13]. Time-frequency spectrum is estimated from EEG signals within a sliding time window and its peak is taken as the detected SSVEP frequency. Gabor Transform is usually adopted as time-frequency analysis tool due to its high precision ratio. The CCA is also applied to detect SSVEP frequency by extracting a narrowband frequency component of SSVEP. The longer sliding window for Gabor Transform and CCA usually results in higher detection accuracy, but suffers from long data-collection and processing times. It also requires long fixation from subjects, causing visual fatigue. This study discusses how to improve the SSVEP detection accuracy and rate.

Empirical Mode Decomposition (EMD) is a pre-processing method of Hilbert-Huang transform (HHT), which was originally proposed by N.E. Huang et al [14]. EMD can decompose a nonlinear and non-stationary time series into its intrinsic mode functions (IMFs). The IMFs were designed to reject unwanted fluctuations according to instantaneous spectra of IMFs. The decomposition method maintains the original shape of the data. Therefore, it is adaptive and highly efficient to analyze the EEG signals that may be nonlinear and/or non-stationary [15-16].

This study discusses the effect of EMD, as a pre-processing step for Gabor Transform and CCA, on the detection accuracy and rate of SSVEP. To be more specific, the EMD is used to extract main components from the original EEG signal. Then the Gabor transform or CCA is employed to detect the frequencies of SSVEPs from the resultant EEG signals. This study also uses the spectral power near both the first and second harmonic frequency of the flickering stimuli to improve the SSVEP detection.

II. METHOD

A. Data Acquisition

Three volunteer subjects with normal or corrected-to-normal vision participated in this study. Subjects were seated in a comfortable chair in front of a computer monitor, and 256-channel EEG data sampled at 2,048Hz, were collected using a Biosemi ActiveTwo system. The visual stimulus was a 3×3 cm flicker rendered at the center of a cathode ray tube (CRT) monitor [17]. The stimulus frequencies ranged from 9Hz to 13Hz with an interval of 1Hz. The experiment consisted of four sessions. Each included five 30s-long trials for the five different stimulus frequencies, which were randomly presented. Subjects were asked to gaze on the flickering stimulus for 30 seconds and then take a ~15s rest after each trial to avoid visual fatigue caused by flickering. There was a several-minute break between two consecutive sessions.

B. EMD

EMD is the core algorithm of HHT that decomposes

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nonlinear and non-stationary signals into various IMFs. The IMFs are obtained by a sifting process, and they should satisfy two conditions: (1) The number of extrema and the number of zero crossings have to be equal or differ at most by one; (2) It has a zero mean.

Given a non-stationary signal $x(t)$, the EMD algorithm comprises the following steps: Step (1) Search all local extrema of $x(t)$, including the minima and maxima, and then fit them with a cubic spline curve to obtain the upper and lower envelop, respectively. Step (2) Calculate the mean value, $m(t)$, of the upper and lower envelops. The difference between the decomposed signal $x(t)$ and $m(t)$ is denoted as $h(t)$:

$$h(t) = x(t) - m(t) \tag{1}$$

If $h(t)$ does not satisfy the above two conditions of IMF, $x(t)$ is replaced with $h(t)$,and repeat the steps(1) and (2). Otherwise, $h(t)$ is an IMF, $c(t)$, and the difference between $x(t)$ and $h(t)$ is denoted as $r(t)$, that is

$$r(t) = x(t) - h(t) \tag{2}$$

Step (3) Take the residual signal $r(t)$ as $x(t)$, and repeat the procedures (1) and (2) to obtain a series of IMF components until $r(t)$ is the one that cannot be further decomposed into an IMF. If the number of IMF is n, we can reconstruct the original signal data from all IMF components $c_i(t)$, i=1,2,...n, as

$$x(t) = r_n(t) + \sum_{i=1}^{n} c_i(t) \tag{3}$$

The collected EEG data are first down-sampled to 256Hz. Each 30s trial is split into six 4s epochs time-locked to the stimulus onset [17]. Then we choose 4 scalp locations over the occipital cortex, the brain area involved in receiving visual signals. These channels are located around Oz in standard 10-20 electrode placement system. The EMD is applied to the signal recorded at each of the 4 channels separately. Fig 1 shows a sample 24s EEG recording from Subject 1.

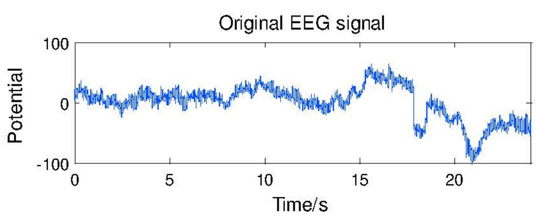

Figure 1. 24sec EEG raw data from subject1.

C. Gabor transform

The Gabor transform of a signal $x(t)$ can be defined by this formula

$$G_D(f,t) = \langle x(t'), g_D^*(t'-t)e^{-2\pi i f t'} \rangle$$
$$= \int_{-\infty}^{+\infty} x(t') \cdot g_D^*(t'-t)e^{-2\pi i f t'} dt', \tag{4}$$

where * denotes complex conjugate, the Gaussian window function g_D is

$$g_D(t) = e^{-\frac{1}{2}\left(\alpha \frac{t-D/2}{D/2}\right)^2}, \tag{5}$$

where D is the width of the window. Function g_D asymptotically approaches to zero with a rate determined by parameter α. When α is larger, the function drops to zero faster.

D. CCA

CCA is a commonly used method for measuring the linear relationship between two sets of multivariate data. This study thus also employed CCA to analyze the EEG [13]. For two multidimensional variables X and Y, X is the 4-channel EEG signals in this study. The set of reference signals Y is chosen as follows:

$$Y = \begin{pmatrix} sin(2\pi f t) \\ cos(2\pi f t) \\ sin(4\pi f t) \\ cos(4\pi f t) \end{pmatrix}, \tag{6}$$

where f is the stimulus frequency.

III. RESULTS

A. IMFs

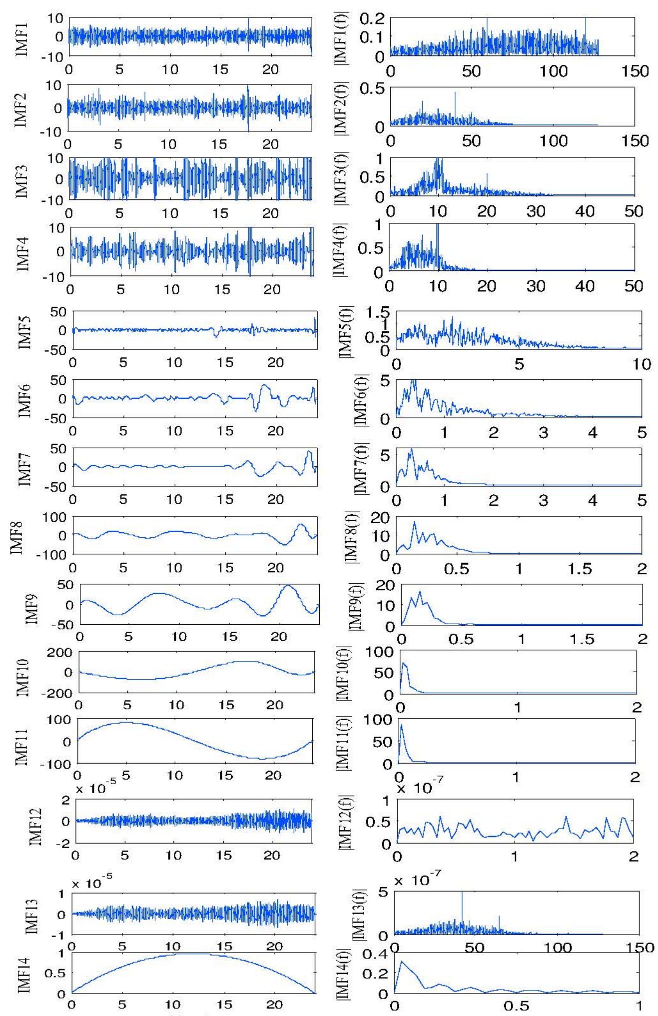

Figure 2. The EMD decomposition of the EEG signal shown in Fig 1 (IMF1 to IMF14) and their powerspectra.

Fig 2 shows the results of EMD decomposition of the signals shown in Fig 1. The signal shown in Fig 1 was decomposed by EMD into IMFs. EMD decomposed the EEG signal into fourteen IMFs. Among them, the IMF1 accounted for the high-frequency (up to 130Hz) activity. The IMF2 corresponded to the 0-60Hz activity. The frequency content of the IMF3 and IMF4 ranged from 0 to 30Hz. Basically, The rest of IMFs represent low-frequency (below 5Hz) activity. This study focused on the first four IMFs as their spectra overlapped with the SSVEP stimulation frequencies (or harmonics), while discarded the low-frequency components (IMF5-14). Particularly, the IMF3 contains the main SSVEP stimulus frequencies involved, this study thus combined IMF3 with IMF1, IMF2, IMF4 to reconstruct four versions of EMD preprocessed signal: (1) the IMF3; (2) the sum of IMF3 and IMF4; (3) the sum of IMF2-4; (4) the sum of IMF1-4, to form the reconstructed EEG signals for SSVEP detection. Although the IMF12 and IMF13 included some high-frequency activities, their amplitude were very small.

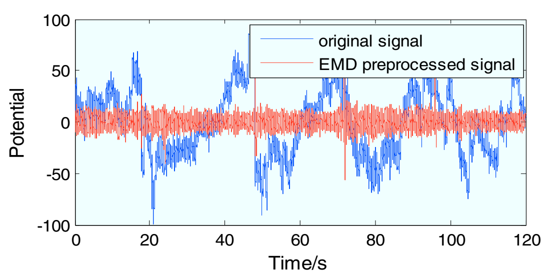

Figure 3. The EEG signals before and after EMD-based denoising.

Fig 3 plots concatenated five segments of 24s data, extracted from different sessions in which the subjects gazed at different stimuli flickering at 10, 12, 11, 9 and 13Hz. The blue trace shows the original EEG signals. The red trace shows the sum of IMF1-4 obtained by the EMD. The EMD preprocessing removed daunting slow drifts in the original EEG recording.

B. *Effect of EMD on SSVEP detection accuracy based on Gabor Transform*

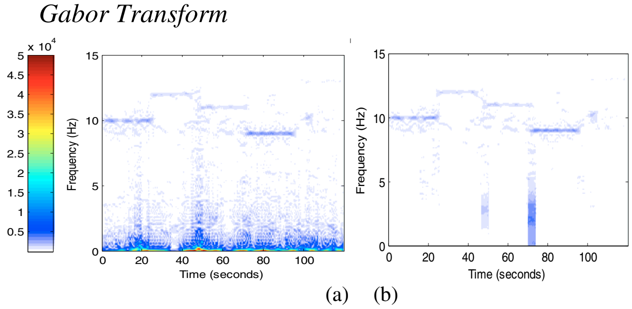

Figure 4. Gabor time-frequency spectrum with D=4s, α=2.5 (a) The original data, (b) The sum of IMF1-4.

Gabor transform was then applied to the preprocessed signals to estimate their spectra. Fig 4 compares the resultant power spectra of original signals and the sum of IMF1-4. The spectra of the original signals included abundant low-frequency activity in Fig 4(a), which was absent in Fig 4 (b). Fig 4 shows that the sequence of the detected SSVEP frequencies was 10-12-11-9-13, which matched the flickering sequence of the visual stimuli. We extract the peak frequencies and take them as the SSVEP frequencies. Fig 5 presents the detected SSVEP frequencies using the original and EMD-preprocessed data with different window sizes, *D*=4s and 2s. The SSVEP detection accuracy using a 2s window (Fig 5 (c) (d)) was lower than that using a 4s window (Fig 5 (a) (b)). Further, EMD preprocessing improved the recognition accuracy at the same window size.

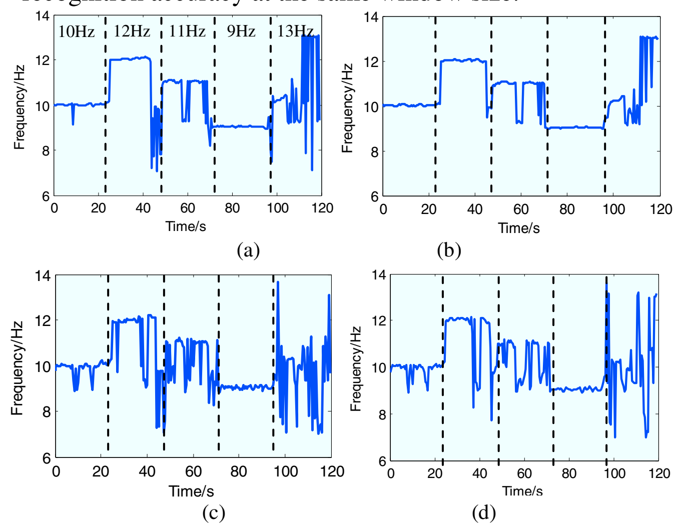

Figure 5. SSVEP frequency detected changes with sliding time in Gabor Transform using (a) The original EEG signal (D=4s,α=2.5,); (b) The EMD-preprocessed signal (D=4s,α=2.5,);(c) The original signal (D=2s,α=2.5);(d) The EMD-preprocessed signal (D=2s,α=2.5).

As visual stimuli induced not only SSVEPs at the flickering frequency, but also its higher harmonics, this study leveraged the higher harmonics to improve detection accuracy. When detecting SSVEP frequency based on the best working channel of 4 channels, this study multiplied the amplitude of fundamental frequency by that of its second harmonic response. Then, the frequency with the highest amplitude product was taken as the SSVEP frequency.

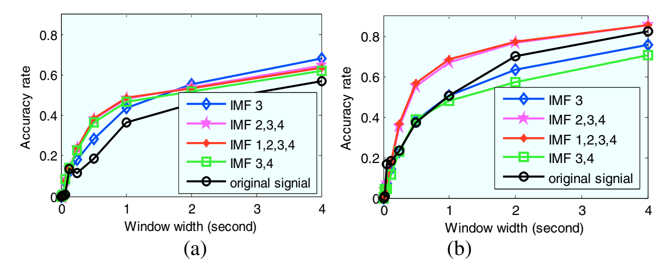

Figure 6. Accuracy rating of identifying target frequency using Gabor transform (a) Without using the second harmonic frequency, (b)Using the second harmonic frequency.

Fig 6 shows that the averaged SSVEP detection accuracy of three subjects as a function of the size of the sliding window. In general, the detection accuracy improved as the size of the sliding window, *D*, increased. Further, EMD preprocessing improved the recognition accuracy at the same window size. For example, at *D*=0.5s, the detection accuracy improved from 24% (using the original signal) to 40% (using the sum of IMF1-4).

Fig 6 also compares the SSVEP detection accuracy with (Fig 6(b)) and without (Fig 6(a)) using harmonics. When the harmonic response was used in the SSVEP detection, IMF1-4 had the best detection rate, while IMF3 and IMF3-4 had a lower accuracy than the original signal because the IMFs did not contain much of the harmonics (Fig 2). In general, using the second harmonic response improved the SSVEP detection performance (Fig 6(a) vs. Fig 6(b)).

C. Effect of EMD on SSVEP detection accuracy based on CCA

This study investigates the effect of EMD and high harmonics on the detection accuracy based on the CCA. Fig 7 shows the averaged accuracy curve of three subjects with and without using harmonic responses. The results showed that the EMD had a less effect on the CCA, compared to that on Gabor Transform. The SSVEP detection accuracy was comparable between using the original and EMD-preprocessed data. It is also evident from comparing Fig 7 (a) and Fig 7 (b) that incorporating the harmonic response could improve the SSVEP detection accuracy.

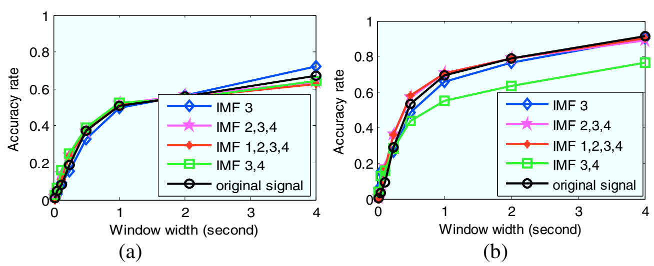

Figure 7. SSVEP detection accuracy rate using CCA (a) Without using the second harmonic response; (b) Using the second harmonic response.

D. Compare Effect of EMD on SSVEP detection accuracy based on Gabor transform and CCA

Fig 8 quantitatively compares the impact of EMD on the Gabor transform and the CCA with *D*=0.5s. It is evident that EMD was a very effective preprocessing tool for the Gabor transform, but had little impact on the CCA. This result suggests that the CCA is less sensitive to the noise. Further, including harmonic responses of the SSVEP fundamental frequency could improve the SSVEP detection accuracy.

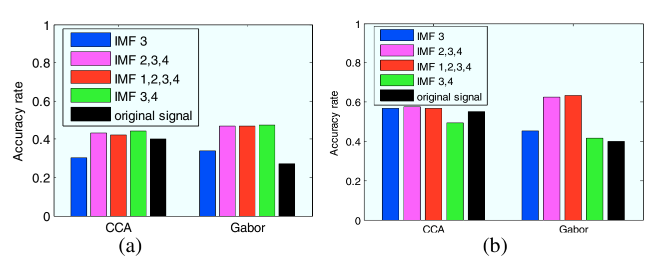

Figure 8. The SSVEP detection accuracy using the CCA and Gabor transform with D=0.5s, α=2.5. (a) No harmonic response was used, (b) Using the second harmonic response.

IV. CONCLUSION

This study systematically tested the impact of EMD on the detection of SSVEP frequencies. EMD decomposed the original EEG signals into IMF components. SSVEP-related IMFs were then extracted for further analysis. Results of this study showed that EMD preprocessing considerably improved the performance of SSVEP detection based on Gabor Transform, but had less influence on the CCA. Further, using the second harmonic response of the fundamental stimulation frequency enhanced the SSVEP detection performance both for the Gabor transform and CCA.

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