TIME-FREQUENCY ANALYSIS OF SCALP EEG BASED ON HILBERT - HUANG TRANSFORM

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Abstract: Electroencephalography (EEG) is the electrical activity of the human brain and thus plays an important role to understand the cognitive function in neuroscience and clinical settings. However, the conventional EEG analyses based on the linear assumption usually are limited to analyzing the nonlinear waveform of brain signals. To address this issue, we present a data-driven method for analyzing scalp EEG signals in the time-frequency domain. Results from both simulation and resting EEG demonstrated that temporal characteristics and non-linear features can be revealed with Hilbert-Huang transform without any prior assumptions. In addition, the Hilbert-Huang transform is less affected by the non-sinusoidal signals.

Key words: Hilbert-Huang transform, Fourier transform, Wavelet, non-linear signal, electroencephalography.

I. INTRODUCTION

Electroencephalography is a non-invasive technique with a high-temporal resolution that enables neuroscientists to study the neurocognitive process in the human brain. Because most cognitive processes such as cognitive, perceptual, emotional, sensory, and working memory processes usually are occurred in milliseconds to a few seconds. Therefore, the EEG is suitable to capture these dynamic cognitive events. The unit of EEG recording is typically microvolts. The early works in electrophysiological research proved that the EEG measurement is a direct reflection of the neuronal oscillation which are rhythmic fluctuations of spiking activity within neuronal populations [1]–[3].

Brain rhythms are categorized into frequency bands including delta (2–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (15–30 Hz), lower gamma (30–80 Hz), and upper gamma (80 –150 Hz). Therefore, the brain oscillation in the time-domain should be turned into the frequency domain or time-frequency domain to acquire more electrophysiological information.

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Manuscript received: 15/11/2021, revised: 27/02/2022, accepted: 16/03/2022.

The Fourier transform is widely used in the frequency analysis of brain rhythms and it is an important technique to understand the collective neural activities in the brain in neuroscience as well as in many other branches of science, engineering, and technology. Conventional time-series data decomposition methods (i.e., Fourier and wavelet transform) are based on additive expansion which assumes that the signal being dealt with is a linear operation. Nevertheless, it is well-known that most brain oscillations have nonlinear and non-stationary characteristics [4], [5] which limit the amount of information extracted by Fourier analysis [5]. The Wavelet transform is a better option for real-world data scales, however, the correct number of wavelets has to be chosen which requires a priori knowledge of the possible frequency bands with increased activity. Fourier and Wavelet also share a problem of blurred representation originating from integral transforms and the challenge of choosing the appropriate time window resolution since increasing time resolution decreases the frequency resolution and vice versa (i.e. uncertainty principle). Thus the high temporal resolution of signals cannot be fully observed with these conventional Fourier-based analyses. To resolve these limitations of traditional methods, Hilbert-Huang transform (HHT) was used as a potential approach for the examination of non-linear signals in this study. HHT consists of two parts: EMD/ensemble empirical mode decomposition (EEMD) and Hilbert spectral analysis (has) [6]. EMD is an adaptive and data-driven manner without the linearity assumption, decomposes the intrinsic nature of the raw signal adaptively into single modes, known as intrinsic mode functions (IMFs). After decomposition, HSA can then be adopted in any IMF to gather the local energy and instantaneous frequency information to produce HHT [6], [7]. Therefore, it partly resolved the flaws in existing spectral analytical methods (such as Fourier analysis and wavelet analysis), which rely on additive expansions and linear assumption [8].

However, the evaluation of HHT performance on the non-sinusoidal oscillation remains unclear. Thus, it is essential to evaluate the effects of non-sinusoidal signals on the traditional method and HHT. The organization of this paper is as follows: In Section II, the introduction of HHT for analyzing the non-sinusoidal signals are presented; in section III, the simulation and experimental results are listed; in section IV, conclusions are described.

II. EEG ANALYSIS BASED ON HILBERT-HUANG TRANSFORM

This technique was originally applied to geophysical signals and has been proved to be useful for nonlinear time-series analysis by using an empirical mode decomposition (EMD) approach. EMD is an adaptive and data-driven manner without the linearity assumption, decomposes the intrinsic nature of the raw signal adaptively into single modes, known as intrinsic mode functions (IMFs). That is, each successive EMD will generate an IMF with lower oscillations than the previous IMF and naturally retain the physical properties of the signal. After decomposition, Hilbert transform can then be used in any IMF to gather the local energy and instantaneous frequency information to produce HHT. Thus, it partly resolved the flaws in existing spectral analytical methods (e.g., Fourier and Wavelet methods), which rely on additive expansions and linear assumption and thus, it has been widely applied to biological, medical, engineering, structural safety monitoring, and climate studies worldwide.

A. Empirical Mode Decomposition:

EMD is an adaptive and data-driven manner without the linearity assumption, decomposes the intrinsic nature of the raw signal adaptively into single modes, known as intrinsic mode functions (IMFs):

$$x(t) = \sum_{j=1}^{n} IMF_j(t) + r_n(t) \qquad (1)$$

1. Let x(t) be the input data, the following steps presents the process used for identifying IMFs: Identify time-series local maxima and minima of x(t)
2. Perform a cubic spline interpolation between all local maxima to compute the upper envelope $e_{max}(t)$ and the lower envelope $e_{min}(t)$.
3. Estimate the mean value of each data time-point between the upper and lower envelope as $m_1(t) = (e_{max}(t) + e_{min}(t))/2$
4. Subtract the mean value from the original signal to provide the local components $h_1(t) = X(t) - m_1(t)$.
5. The sifting procedure was applied to guarantee the component $h1(t)$ satisfied the condition to be an IMF. The stopping criterion of the sifting process is defined in the Eq. (2) by using a standard deviation (SD), δ , computed from the two consecutive components as:
6.

$$\delta = \sum_{t=0}^{N} \frac{\left|h_{1(m-1)}(t) - h_{1(m)}(t)\right|^2}{h^2{}_{1(m-1)}(t)} \qquad (2)$$

A threshold value for SD can be set between 0.2 and 0.3 to stop the sifting process [6]. The process is repeated until only a monotonic time-series or residue $r_n(t)$ remains, indicating the trend of x(t). Customized Matlab (MathWorks) scripts with ensemble EMD code provided by the Research Center for Adaptive Data Analysis of National Central University, Taiwan was used for applying HHT [9], [10].

B. Hilbert spectral analysis:

After decomposition, the IMFs obtained by EEMD ensure the performance of Hilbert transform on each IMF with its clear definition of an instantaneous phase and amplitude to produce HHT. Thus, Hilbert transform is applied to each IMF and can be expressed as Eq. (3):

$$H[\text{IMFi}(t)] = \frac{1}{\pi} PV \int_{-\infty}^{+\infty} \frac{\text{IMFi}(\tau)}{t-\tau} d\tau \qquad (3)$$

Where PV is the Cauchy Principal Value, thus, a complex analytic signal IMF*(t) can be derived and expressed as Eq. (4):

$$IMFi^*(t) = \text{IMFi}(t) + iH[IMFi(t)] = A(t)e^{i\theta(t)} \qquad (4)$$

where A(t), θ(t) are defined as the amplitude function and phase of IMFi(t), respectively.

III. RESULTS

A. *Simulation results*

To evaluate the effectiveness in analyzing the nonlinear signals of the proposed approach, in this section, the current study evaluated the effects of nonlinear signals on the performance of HHT compared with FFT and Wavelet (WL).

Case 1:

Figure 1 shows the noiseless 14 Hz sinusoidal signal (*S*, black line) and its power spectrum in the frequency domain (FFT) and time-frequency domain (i.e., WL and HHT). The results show that the FFT spectrum displays an amplitude at a single peak of 14 Hz while WL and HHT enable to show amplitude increases at 14 Hz across time domain.

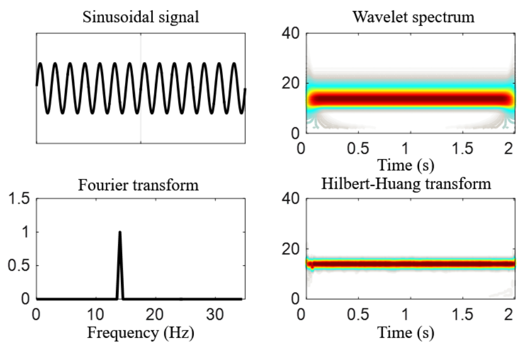

Figure 1. Power spectra of noiseless sinusoidal signal analyzed by traditional methods and Hilbert-Huang transform.

Case 2:

To validate the effect of non-linear signals on these methods, the current study generated a 14 Hz signal with non-linear signals by controlling the degree of non-linearity [11]. The non-linear signal was generated as Eq. (5):

$$X(t) = U_w\sqrt{1-r^2}\,\frac{\left[\sin(\omega t) + \frac{r\sin\phi}{1+\sqrt{1-r^2}}\right]}{1 - r\cos(\omega t + \phi)} \quad (5)$$

Where U_w represents amplitude, ω represents the angular frequency and ϕ is phase $(-\pi/2 \le \phi \le \pi/2)$. The parameter r (-1 < r < 1) is determined as the degree of non-linearity and is set to 0.4 (i.e., the signal is now highly distorted and non-linear). Figure 2 displays the outcomes of FFT, WL, and HHT for the simulated data. In the frequency domain, a clear peak at 14 Hz was present for FFT. However, in addition to the frequency of 14 Hz, FFT also displays the spurious harmonics in the spectrum. Similar to the results of FFT, Wavelet decomposed the non-linear signals into several harmonics as shown in Figure. In contrast, HHT shows clearly the physical meaning of the signal with a varying amplitude at a broadband frequency (10-18 Hz).

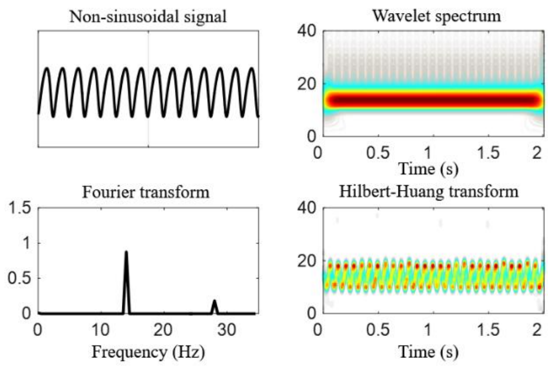

Figure 4. Power spectra of noiseless sinusoidal signal analyzed by traditional methods and Hilbert-Huang transform.

Case 3:

These approaches were then validated by analyzing the amplitude modulation (AM), in which one sinusoidal signal was a carrier oscillation ($f_c = 14$ Hz) and the modulating signal was selected to 2 Hz ($f_m = 2$ Hz). Figure3 shows the power spectra of FFT, WL, and HHT for this simulated data. The FFT spectrum shows an amplitude at a peak of 14 Hz and two side-bands while WL and HHT enable to show the varying amplitudes at 14 Hz across time domain, indicating that these methods were capable to capture the physical meaning of the amplitude modulation.

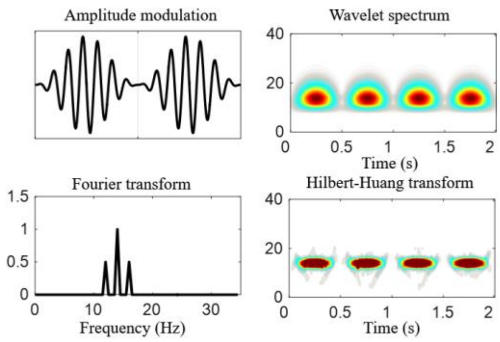

Figure 2. Power spectra of noiseless AM signal analyzed by traditional methods and Hilbert-Huang transform.

Case 4:

In addition to the above example, here, this study also discusses another case of a non-sinusoidal signal using an exponent of 2 (i.e., $2^{AM(t)}$). Although Fourier transform could obtain the fundamental frequencies. That is the amplitude at a peak of 14 Hz and two sidebands. This non-sinusoidal waveform shape also produced multiple harmonics. Similar to FFT, Wavelet shows multiple harmonics. In addition, Wavelet can not fully display the varying amplitudes over time as shown in HHT (Figure 4).

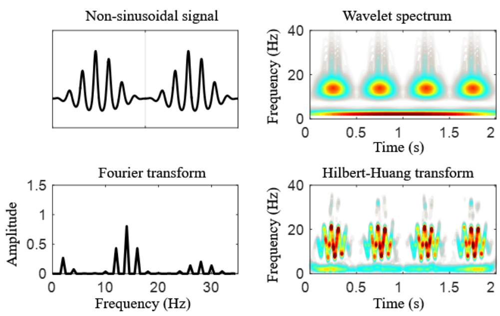

Figure 3. Power spectra of non-linear AM signal analyzed by traditional methods and Hilbert-Huang transform.

B. Experimental results

Instead of the synthesized data, here real-time EEG data showing the Steady-state visually evoked potential (SSVEP) phenomenon was analyzed to validate the capability of the proposed methods as shown in the simulation data. The SSVEPs data of single-subject elicited by 3-Hz flicker at Oz channel used in this study were reported originally by Juan et al., 2021 [12] . Figure 5 shows the power spectrum in the frequency domain (FFT) and time-frequency domain (i.e., WL and HHT). That is, the power increase was observed at 6 Hz and 9 Hz in both frequency domain and time-frequency domain.

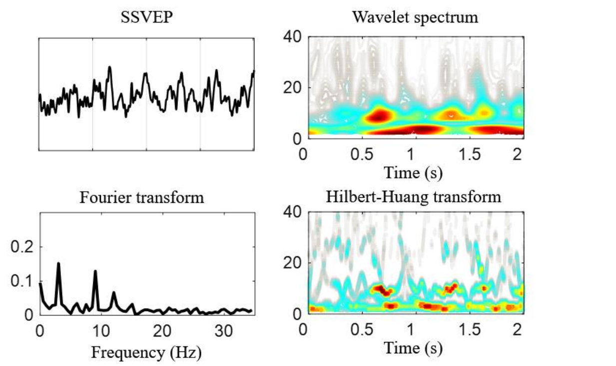

Figure 5. The power spectra of a single subject SSVEPs induced by 3-Hz flicker.

IV. CONCLUSION

In this study, we have confirmed the Hilbert-Huang transform as an effective approach to analyze the non-linear oscillations. We evaluated the performance of this method compared to the previous method (i.e., FFT and Wavelet). The results in numerical experiments using simulation and electrophysiology data show that the Fourier transform, Wavelet, and Hilbert-Huang transform provide clear power spectra. However, since FFT and Wavelet may be limited to analyzing the non-sinusoidal signals, these methods were difficult to confirm the real phenomena in the brain oscillations. In contrast, the HHT were less affected by the non-sinusoidal waveform, thus, the findings of the HHT method provide clear physiological evidence in support of the existence of real phenomena in the human brain.

ACKNOWLEDGMENTS

THIS WORK WAS SPONSORED BY POSTS AND TELECOMMUNICATIONS INSTITUTE OF TECHNOLOGY, VIETNAM (GRANT NO. 04-HV-2021-RD_ĐT2).

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PHÂN TÍCH PHỔ THỜI GIAN VÀ TẦN SỐ CỦA TÍN HIỆU ĐIỆN NÃO ĐỒ DỰA TRÊN PHƯƠNG PHÁP HILBERT HUANG TRANSFORM

Abstract: Tín hiệu điện não là một hoạt động điện của não người và do đó đóng một vai trò quan trọng để hiểu được chức năng nhận thức và được sử dụng trong lâm sàng. Tuy nhiên, các phương pháp phân tích tín hiệu điện não truyền thống dựa trên giả sử tuyến tín thường bị giới hạn khi phân tích một dạng tín hiệu não phi tuyến. Để giải quyết điều này, nghiên cứu này sử dụng một phương pháp phân tích hướng dữ liệu cho việc phân tích điện não đồ trong miền thời gian và tần số. Kết quả từ cả tín hiệu mô phỏng và điện não đã minh họa rằng các tính năng phi tuyến và biến động thời gian có thể được làm sáng tỏ dùng phương pháp Hilbert-Huang transform mà không sử dụng giả thuyết đã biết. Thêm vào đó, phương pháp HilbertHuang transform ít bị ảnh hưởng bởi tín hiệu phi tuyến.

Nguyễn Trọng Kiên, Tốt nghiệp Thạc sĩ Kỹ thuật Viễn thông năm 2014 tại Học viện Công nghệ Bưu chính Viễn thông. Nhận học vị Tiến sỹ ngành Khoa học Thần kinh nhận thức năm 2020 tại Đài Loan. Hiện là giảng viên khoa Kỹ thuật Điện tử 2, Học viện Công nghệ Bưu chính Viễn thông, cơ sở tại TP. Hồ Chí Minh. Lĩnh vực nghiên cứu: Xử lý tín hiệu y sinh không xâm lấn, thiết kế hệ thống nhúng, thiết bị y sinh.
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Nguyễn Trọng Huân, sinh ngày 17/10/1986. Tốt nghiệp đại học tại Đại học Sư phạm Kỹ thuật TP.HCM vào năm 2010 và nhận bằng Thạc sĩ tại Học viện Công nghệ Bưu chính Viễn thông vào năm 2013. Hiện công tác tại Khoa Kỹ thuật Điện tử 2, Học viện Công nghệ Bưu chính Viễn thông cơ sở TPHCM. Lĩnh vực nghiên cứu: hệ thống nhúng, thiết kế vi mạch. Email: huannt@ptithcm.edu.vn.