

HHT-Based Time-Frequency Analysis Method for Biomedical Signal Applications

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Abstract: - Fourier transform, wavelet transformation, and Hilbert-Huang transformation (HHT) can be used to discuss the frequency characteristics of linear and stationary signals, the time-frequency features of linear and non-stationary signals, the time-frequency features of non-linear and non-stationary signals, respectively [1-6]. HHT is a combination of empirical mode decomposition (EMD) and Hilbert spectral analysis. EMD uses the characteristics of signals to adaptively decompose them to several intrinsic mode functions (IMFs). Hilbert transforms (HTs) are then used to transform the IMFs into instantaneous frequencies (IFs), to obtain the signal's time-frequency-energy distributions. HHT-based time-frequency analysis can be applied to natural physical signals such as earthquake waves, winds, ocean acoustic signals, mechanical diagnosis signals, and biomedical signals. In previous studies, we examined mobile telemedicine, chaos-based medical signal encryption, HHT-based time-frequency analysis of the electroencephalogram (EEG) signals of clinical alcoholics, and sharp wave based HHT time frequency features [7-21]. In this chapter, we discuss the application of HHT-based time-frequency analysis to biomedical signals such as EEG, and electrocardiogram (ECG) signals.

Key-Words: Hilbert-Huang transformation, empirical mode decomposition, intrinsic mode functions, instantaneous frequencies, time-frequency-energy distributions, biomedical signals, electroencephalogram, electrocardiogram.

1 Electroencephalograms (EEGs)

Much of the information carried by electroencephalogram (EEG) signals is still not understood. Lin et. al. [19, 20] discussed the application of the Hilbert-Huang transform (HHT) method to FP1 EEG signals obtained from an alcoholic observer viewing a single picture, and for the same observer viewing two different pictures. They used the intrinsic mode functions (IMFs), instantaneous frequencies (IFs), and Hilbert energy spectra to analyze the energy-frequency-time distributions of normal and alcoholic observers watching two different pictures. They found that the maximum amplitude of the EEG signals recorded from normal control observers was larger than that from alcoholic observers. The numbers of brain cells that were stimulated and emitted a higher voltage was greater in alcoholic observers than in the normal control observers. Further, compared with normal observers, the amplitude of the IMFs of the alcoholics' clinical EEG signals was low. They also found that the IFs of alcoholic subjects were larger than those of normal observers. With respect to the variation in the energy-frequency distribution of the HMFs of alcoholic and normal observers, Lin

et. al. [19, 20] demonstrated that the high-energy signals of both groups are distributed in the low-frequency band. The energy-frequency distribution of the IMFs of the alcoholics' clinical EEG signals was larger than that of normal observers. HHT-based method have proven useful in the study of epilepsy. Lin et. al. [21] obtained a sharp (I) EEG signal from the T3 channel for a clinical patient suffering from epilepsy. In this case, a sharp wave was generated in the interval between 0.324 s and 0.444 s, it had a length of 120 ms, and an amplitude of 73.63 mV. The authors present the IMFs, IF, and time-frequency-energy distributions for the sharp and normal waves. Clear energy-frequency-time variations in sharp and normal waves with a transmission bit error rate (BER) of 10^{-7} were demonstrated. HHT analysis revealed four IMFs and a residual function of sharp and normal waves. Analysis results showed that the ratios of the energy of a sharp wave represented by IMF3 or IMF4 to the total energy of a sharp wave, the ratio of the energy of a normal wave represented by IMF4 to the total energy of a normal wave, and the ratio of the energy of a normal wave represented by the residual function to the total energy of a normal wave are 34.55%, 33.73%, 43.25%, and

37.63%, respectively. The energy of a sharp wave represented by IMF4 in the δ band (0.5Hz-4Hz) is 98.4% of the total energy of this wave. The ratio of the energy of a normal wave represented by IMF4 in the δ band is 82.2% of the total energy of a sharp wave represented by IMF4. The mean IF of a sharp wave represented by IMF4 is smaller than that of a normal wave represented by IMF4.

Researchers have also used HHT-based methods to examine sleep EEG signals. Yang et.al. [22] proposed an HHT-based spindle-detection approach. EMD is employed to decompose sleep EEGs into several IMFs, and the high-resolution time-frequency Hilbert spectrum is used to extract the features of the sleep EEGs. Experiments show that the HHT-based spindle-detection approach is suitable for sleep EEG signals. Causa et. al. [23] presented an HHT-based time frequency methodology for detecting and characterising sleep spindles (SSes) in EEG signals of healthy ten-year-old children. The experiments include 27 training recordings, 10 validation recordings, and 19 testing recordings from the children's all-night polysomnographic recordings. Causa et. al. [23] used EMD and HHT to generate SS candidates, and determine the thresholds of the maximum and minimum values for instantaneous amplitude and instantaneous frequency for an SS event. Simulation results show a 92.2% sensitivity for non-REM stage 2 sleep.

Various other applications of HHT-based methods to EEG signals have been demonstrated. Chen et.al. [24] used the concept of general-purpose computing on a graphics processing unit (GPGPU), combined with parallelized ensemble EMD (EEMD), and the Hilbert-Huang spectral entropy [25] to develop a real-time EEG analysis method for use on patients under anaesthesia. Chen et.al. [26] analysed the EEG signals of epilepsy patients using the Gabor transform and the frequency band relative intensity ratio; these methods performed well at both time-frequency scales, and clearly differentiated the epileptics periods, including the interictal, preictal and ictal periods. Zhang et.al. [27] used EMD to decompose EEG signals into several IMFs, they used different thresholds to treat and reconstruct the IMFs to achieve de-noising. Rutkowski et.al. [28][29] developed a new method of extending a single channel EMD approach to EEG signal analysis with steady-state responses for application to brain-computer interface (BCI) detection. They used an analysis of the correlations between the Hilbert-Huang frequency and amplitude domains of multichannel, high-noise EEG signals to identify different brain states related to stimuli. In addition,

they discussed the Euclidean, maximum Manhattan, and Canberra distances of the IMFs.

2 Electrocardiograms (ECGs)

The electrocardiogram (ECG) is an important biomedical signal for the measurement of cardiac activity. Muscle contraction, baseline wander, and power-line interference will interfere with the ECG signals during measurement. Karagiannis et.al., [30], proposed a modified EMD method for extracting the IMFs of time series of various lengths, and applied it to the de-noising of synthetic ECG signals. The modified EMD method includes three steps. First, the statistical significance of a set of IMFs is investigated; second, the computation time of the EMD method applied to biomedical signals is measured, and third, the size of the IMF set is monitored. A monitor mode and two diagnostic modes are used in ECG operation. The cutoff frequencies of the high-pass and low-pass filters are 0.5-1Hz and 40Hz, respectively, in the monitor mode. In the diagnostic modes, the cutoff frequencies of the high-pass and low-pass filters are 0.05 Hz, and 40-150Hz, respectively. Karagiannis et.al., [31] discussed the number of IMFs as a function of the signal-to-noise ratio (SNR) and the length of a simulated white Gaussian noise corrupted ECG time series. The authors also determined the computation time of the modified EMD algorithm.

Other noise-reduction methods have been developed as well. Chang et.al., [31] proposed the partial reconstruction of an EEMD-derived IMF combined with a Wiener Filter to remove ECG noise. Their simulation results showed that the EEMD exhibited better noise-filtering performance than EMD or a finite impulse response (FIR) Wiener filter.

HHT-based time-frequency analysis is also used to characterize ECG signals. John et.al., [32] used EMD to decompose normal and various abnormal rhythms in ECG signals, and then used a chaos analysis method to discuss the resulting IMFs. The Lyapunov exponent, a positive entropy, and a non-integer correlation dimension chaotic parameter are adopted; the results show significant differences between the normal sinus rhythm and various sets of abnormalities. The authors discussed an effective way to characterise non-linearities in non-stationary ECG signals by using empirical mode decomposition and chaos analysis methods. Wu et.al., [3] used EMD to decompose ventricular fibrillation (VF) ECG signals into several IMFs, and calculated the instantaneous phase of the resulting IMFs by using a

Hilbert transform. The phase statistics were analyzed to estimate the correlation between the characteristic properties of VF ECG signals, and the corresponding consequences. This method can be used to distinguish fatal and non-fatal VF.

3. Conclusion

HHT-based analysis methods are widely applied to biomedical signals; this paper describes examples of these applications. HHT-based time-frequency analysis has been applied to the EEGs of alcoholic, sharp-wave EEGs in epilepsy, sleep EEG signals, anaesthesia EEG signals, EEG de-noising, BCI detection, brain activity feature extraction, ECG de-noising, VF ECG signals, abnormal ECG feature extraction,. From these examples, we can see how the HHT time-frequency analysis is used to detect, analysis, and processing, biomedical signals and develop new approaches to treating various illnesses.

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