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Hilbert–Huang transformation-based time-frequency analysis methods in biomedical signal applications

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Abstract

Hilbert–Huang transformation, wavelet transformation, and Fourier transformation are the principal time-frequency analysis methods. These transformations 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. The Hilbert–Huang transformation is a combination of empirical mode decomposition and Hilbert spectral analysis. The empirical mode decomposition uses the characteristics of signals to adaptively decompose them to several intrinsic mode functions. Hilbert transforms are then used to transform the intrinsic mode functions into instantaneous frequencies, to obtain the signal's time-frequency-energy distributions and features. Hilbert–Huang transformation-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 Hilbert–Huang transformation-based time-frequency analysis of the electroencephalogram FP1 signals of clinical alcoholics, and 'sharp I' wave-based Hilbert–Huang transformation time-frequency features. In this paper, we discuss the application of Hilbert–Huang transformation-based time-frequency analysis to biomedical signals, such as electroencephalogram, electrocardiogram signals, electrogastrogram recordings, and speech signals.

Keywords

Biomedical signals, electroencephalogram, electrocardiogram, empirical mode decomposition, Hilbert–Huang transformation, intrinsic mode functions, instantaneous frequencies, other medical signals, time-frequency-energy distributions

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Introduction

Hilbert–Huang transformation (HHT) is an interesting field of signal analysis research that was first proposed by Huang et al.[1–2]; subsequently, several papers[1–4] have discussed the HHT concept. HHT is a combination of empirical mode decomposition (EMD) and Hilbert spectral (HS) analysis and can be used to examine the time-frequency characteristics of non-linear and non-stationary signals. The EMD uses the characteristics of signals to adaptively decompose them into several intrinsic mode functions (IMFs) such as completeness, orthogonality, locality, and adaptiveness. The number of IMFs depends on the HHT-based time-frequency feature. Hilbert transforms (HT) are then used to transform the IMFs into instantaneous frequencies (IFs) in order to obtain the signal's time-frequency-energy distributions and features. In contrast, Fourier transforms can be used to discuss the frequency and time-frequency characteristics of linear signals, while wavelet transformations can be used to discuss the frequency characteristics of stationary signals and time-frequency features of non-stationary signals. The resolution of the HHT-based time-frequency analysis methods is better than that of wavelet-based methods. Wu and Huang[3] discussed the advantages and disadvantages of using HHT as compared with other time-frequency methods and described its complexity and efficient implementations. However, Wu and Huang[3] did not provide a detailed study of the HHT analysis methods for several biomedical signal applications.

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In previous studies, we have examined mobile telemedicine,[5–11] chaos-based medical signal encryption,[12–16] HHT-based time-frequency analysis of the electroencephalogram (EEG) signals of clinical alcoholics, and sharp wave-based HHT time frequency features.[17–19] In this paper, we investigate several HHT analysis methods for biomedical signal applications in detail. The HHT-based time-frequency analysis method is described in HHT-based time-frequency analysis method, while HHT-based time-frequency analysis methods applied to EEG, electrocardiogram (ECG), and other medical signals are presented. Finally, the paper then presents conclusions.

HHT-based time-frequency analysis method

In the HHT temporal time-frequency-energy signal analysis method[1–4] the following procedure is employed for analysing the IMF using EMD.

Step 1: Initially assume $r_o = x(t)$, $x(t)$ is real, and $i = 1$.

Step 2: Analyse the ith IMF;

(a) initially assume $h_{i(k-1)} = r_i$, k = 1;
(b) analyse the local maximum and minimum for $h_{i(k-1)}$;
(c) construct the upper-limit and lower-limit envelope for $h_{i(k-1)}$ by performing cubic spline interpolation;
(d) calculate the-mean $m_{i(k-1)}$ of the upper-limit and lower-limit envelope for $h_{i(k-1)}$;
(e) $h_{ik} = h_{i(k-1)} - m_{i(k-1)}$;
(f) determine whether h_{ik} complies with conditions 1 and 2?

if h_{ik} is the IMF, then $IMF_i = h_{ik}$; alternatively, refer to step (b) and consider $k = k + 1$;

In such cases, IMF is defined by 2 conditions.

Condition 1: the number of the 'zero crossing' and that of the 'local extreme value' are smaller than one.

Condition 2: the mean of any point is the average of the local maximum and minimum envelope.

Step 3: define $r_{i+1} = r_i - \mathrm{IMF}_i$;

Step 4: if r_{i+1}, the number of the 'zero crossing' and that of the 'local extreme value', is larger than one, refer to step 2 or consider that the analysis procedure is complete and that r_{i+1} is the residual signal.

In addition, the HHT-based time-frequency analysis scheme is performed on the basis of four assumptions.

Assumption 1: at least two extreme values for the signals, i.e. maximum and minimum values, are present.

Assumption 2: the scale size of the characteristic time is selected according to the extreme values and the temporal interval. In addition, the characteristic time is a reference time window that we wish to analyse.

Assumption 3: if the data to be analysed have no extreme values but contain identifiable points that can be expressed as extreme points of single or multiple analyses, and accompany an increase in the number of analyses, the maximum/minimum points gain significance.

Assumption 4: the final result should be the sum of the above-stated composition. Thus, the single signal can be defined as function $x(t)$, and function $x(t)$ can be expressed as the following empirical mode function to analyse the IMF

$$x(t) = \sum_{i=1}^{n} IMF_i(t) + r(t) \tag{1}$$

where, $\mathrm{IMF}_i(t)$: the ith IMF equals $r(t)$: attribution function (residual)

Then

$$z(t) = x(t) + jy(t) = x(t) + jHT\{x(t)\} = a(t)e^{j\theta(t)}$$

HT{}:Hilbert Transformation

$$a(t) = \sqrt{x^2(t) + y^2(t)}$$
$$\theta(t) = \arctan\left(\frac{y(t)}{x(t)}\right) \tag{2}$$

Thus, the IF of a signal can be analysed using the following equation

$$f(t) = \frac{1}{2\pi}\frac{d\theta(t)}{dt} \tag{3}$$

By using this method, the time-frequency characteristic vector of the signal can be acquired, and the frequency characteristics, amplitude characteristics, time-dependent temporal–spatial frequency correlation, and correlation of the signal to the characteristics can be analysed. Furthermore, this approach can be used to determine statistically common and abnormal points, generalize a standard by comparison with a normal sample, augment the efficiency of observations, and analyse the HHT time-frequency-energy characteristics corresponding to the signal.

EEGs

Much of the information carried by EEG signals is still not understood. Lin et al.[17,18] discussed the application of the HHT method to FP1 EEG signals obtained from an alcoholic subject viewing a single picture, and for the same subject viewing two different pictures. They used the IMFs, IFs, and Hilbert energy spectra to analyse the frequency-time-energy distributions of normal and alcoholic subjects watching two different pictures. The alcoholic subject has a long-term drinking problem and may suffer from alcoholism.

They found that the maximum amplitude of the EEG signals recorded from normal control subjects was larger than that from alcoholic subjects. The numbers of brain cells that were stimulated and the EEG signal was greater in alcoholic subjects than in the normal control subjects. Further, compared with normal subjects, 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 subjects. With respect to the variation in the energy-frequency distribution of the Hilbert-marginal frequencies (HMFs) of alcoholic and normal, Lin et al.[17,18] discussed the application of the HHT method to FP1 EEG signals obtained from an alcoholic subject viewing a single picture, and for the same observer viewing two different pictures. They used the IMFs, IFs, and Hilbert energy spectra to analyse the energy-frequency-time distributions of normal and alcoholic subjects watching two different pictures. The alcoholic subject has a long-term drinking problem and may suffer from alcoholism. They found that the maximum amplitude of the EEG signals recorded from normal control subjects was larger than that from alcoholic subjects. The numbers of brain cells that were stimulated and the EEG signal was greater in alcoholic subjects than in the normal control subjects. Further, compared with normal subjects, 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 subjects. Lin et al.[17,18] 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. The HHT-based method has proven useful in the study of epilepsy. Lin et al.[19] 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 considered using a wireless platform to transmit normal and sharp waves. The bit error rate (BER) of normal and sharp waves at the receiving end was 10^{-7}. The received normal and sharp waves with a BER of 10^{-7} were dismantled with EMD into a number of IMFs and a residue function. The authors present the IMFs, IF, and time-frequency-energy distributions (TFED) for the sharp and normal waves with a transmission BER of 10^{-7}. In addition, clear time-energy-frequency variations in sharp and normal waves with a transmission BER of 10^{-7} were demonstrated.

HHT analysis revealed four IMFs and a residual function of sharp and normal waves. Analysis results show 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 (0.5–4 Hz) 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.[20] 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.[21] presented an HHT-based time-frequency methodology for detecting and characterising sleep spindles (SSs) 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.[21] 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-rapid eye movement (REM) stage 2 sleep.

Various other applications of HHT-based methods to EEG signals have been demonstrated. Chen et al.[22] 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 (HHSE)[23] to develop a real-time EEG analysis method for use on patients under anaesthesia. Chen et al.[24] analysed the EEG signals of epilepsy patients using the Gabor transform (GT) and the frequency band relative intensity ratio (FBRIR); 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.[25] used EMD to decompose EEG signals into several IMFs with different thresholds to treat and reconstruct the IMFs to achieve de-noising. Rutkowski et al.[26,27] 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 (MMCDI). Saito et al.[28] used EMD and the amplitude variation in the Hilbert–Huang spectrum (HHS) with respect to a frequency range to analyse EEG data from quasi-brain-dead patients. The results of their analysis show that the methods performed well in extracting a signal that represents brain activity. HHT-based analysis methods and the system features of EEG signal applications are summarized in Table 1. '○' denotes the analysis technology used in previous studies and the HHT method. The results in the table show a number of methods that involve using HHT with the integration of other analysis technology to obtain brain wave characteristics.

Table 1. HHT-based analysis methods and the system features of EEG signal applications.

	Applications	IMFs	Thresholds	IFs	HHES	Correlations	EMD	EEMD	GT	FBRIR	BER	Euclidean	TFED	SC	HHSE	MMCDI	GUGPU
Lin et al.[17,18]	Alcoholic FP1 EEG signals	○		○	○		○						○				
Lin et al.[19]	Obtains a sharp (I) EEG signal from the T3 channel for a clinical patient suffering from epilepsy	○		○			○				○		○	○			
Yang et al.[20]	An HHT-based spindle-detection approach for sleep EEGs	○		○	○		○						○				
Causa et al.[21]	Detecting and characterizing sleep spindles (SSs) in EEG signals of healthy ten-year-old children	○		○			○							○			
Chen et al.[22]	Real-time EEG analysis method for use on patients under anaesthesia	○		○				○							○		○
Chen et al.[24]	Analyses the EEG signals of epilepsy patients and clearly differentiates the epileptics periods, including the interictal, preictal and ictal periods	○		○			○		○	○			○	○			
Zhang et al.[25]	HHT-based EEG de-nosing	○	○				○										
Rutkowski et al.[26,27]	EEG signal analysis with steady-state responses for application to BCI detection	○		○		○	○					○				○	
Saito et al.[28]	Analyses EEG data from quasi-brain-dead patients	○		○	○		○						○				

Note: for abbreviation definitions, please see Appendix 1.

Studies[17–28] used IMF technology; the critical parameter method was adopted in Zhang et al.[25]; Lin et al.,[17–19] Yang et al.,[20] Causa et al.,[21] Chen et al.,[22,24] Li et al.,[23] Rutkowski et al.,[26,27] and Saito et al.[28] employed IMF technology; Lin et al.,[17–18] Yang et al.,[20] and Saito et al.[28] used Hilbert–Huang energy spectra (HHES) technology; Rutkowski et al.[28,29] adopted correlations technology; Lin et al.,[17–19] Yang et al.,[20] Causa et al.,[21] Zhang et al.,[25] Rutkowski et al.,[26,27] and Saito et al.[28] employed EMD technology; Chen et al.[22] used EEMD technology; Chen et al.[26] adopted GT and FBRIR technologies; Zhang et al.[25] discussed the relationship between the transmission BER and the HHT characteristics of biomedical signals; Rutkowski et al.,[26,27] examined Euclidean technology; TFED technology was adopted in Lin et al.,[17–19] Yang et al.,[20] and Saito et al.[28]; statistical characteristics (SC) technology was applied in Lin et al.,[19] Causa et al.,[21] and Chen et al.[24]; HHSE technology was used in Chen et al.[22]; MMCDI was adopted by Rutkowski et al.,[26,27]; and GUGPU was employed by Chen et al.[22]. Using these studies, we can examine the following methods that are commonly used to obtain and determine brain wave frequency characteristics: HHT frequency analysis integrated with the critical parameter method, HHES, correlations, GT, FBRIR, BER, Euclidean, TFED, SC, HHSE, MMCDI, and GUGPU.

ECGs

The 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 and Constantinou[29] proposed a revised 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 IMFs set are monitored and diagnosis. In addition, the monitor and diagnostic modes were developed using filters with cut-off frequencies. The cut-off frequencies of the high-pass and low-pass filters are 0.5–1 Hz and 40 Hz, respectively, in the monitor mode. In the diagnostic modes, the cut-off frequencies of the high-pass and low-pass filters are 0.05 Hz, and 40–150 Hz, respectively. Karagiannis and Constantinou[29] 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 and Liu[30] 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. Chang[31] proposed a novel noise filtering algorithm based on EEMD for removing artefacts in ECG traces. Their simulation results showed that a high level of noise reduction is the major advantage of the EEMD-based filter, especially on arrhythmic ECGs.

HHT-based time-frequency analysis is also used to characterize ECG signals. John and Sun[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 characterize non-linearities in non-stationary ECG signals by using EMD and chaos analysis methods. Wu and Huang[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 (PS) were analysed 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. HHT-based analysis methods and the system features of ECG signal applications summarized in Table 2. '○' denotes the analysis technology used in previous studies and the HHT method. From Table 2, we see that studies by Wu and Huang,[3] Karagiannis and Constantinou,[29] Chang and Liu,[30] Chang,[31] and John and Sun[32] used IMF technology. A revised EMD method was applied in Karagiannis and Constantinou[29] and Chang[31]; Karagiannis and Constantinou[29] used the high-pass and low-pass filters, and SNR methods; an EEMD scheme was employed by Chang and Liu,[30] and Chang[31]; Chang and Liu[30] adopted Wiener Filter technology; EMD were adopted by Wu and Huang[3] and John and Sun[32]; the chaos analysis method was used in John and Sun[32]; HT, PS, and correlation methods were employed in Wu and Huang.[3] Using these studies, we can examine the following methods that are commonly used to obtain and determine ECG features analysis: HHT frequency analysis integrated with the IMFs, a revised EMD, highpass and lowpass filters, SNR, EEMD, Wiener Filter, EMD, chaos analysis, HT, PS, and correlation.

Other medical signals

Liao et al. [33] used EMD and EEMD algorithms to improve the contrast-to-tissue ratio (CTR) of pulse-inversion (PI)-based ultrasound non-linear imaging at both the fundamental and second harmonic frequencies. Simulation results show that EMD can effectively suppress the amplitude of the tissue signal while

Table 2. HHT-based analysis methods and the system features of ECG signal applications.

	Applications	IMFs	Revised EMD method	High-pass and low-pass filters	SNR	EEMD	Wiener Filter	EMD	Chaos analysis	HT	PS	Correlation
Karagiannis and Constantinou[29]	De-noising of synthetic ECG signals	○	○	○	○							
Chang and Liu[30]	Remove ECG noise	○				○	○					
Chang[31]	Remove artefacts in ECG traces	○	○			○						
John and Sun[32]	Decompose normal and various abnormal rhythms in ECG signals	○						○	○			
Wu and Huang[3]	Decompose VF ECG signals	○						○		○	○	○

Note: for abbreviation definitions, please see Appendix 1.

extracting the non-linear oscillations of microbubbles for certain IMF components. The authors also used the EEMD algorithm to markedly improve the CTR in both PI fundamental imaging and PI second-harmonic imaging. The EEMD-based CTR in second-harmonic imaging is significantly higher than the EMD-based CTR in second-harmonic imaging, because EEMD is effective at separating the tissue harmonic signal and contrast harmonic signal at a similar scale. EEMD is more suitable for imaging methods in which significant overlap occurs between the spectral components of the bubble and tissue signals.

Wu et al.[34] used HHT-based radial arterial waveform analysis and EEMD diabetic control in the elderly, IMF5 showed a discernible diastolic peak, and significant differences appeared between the reflection index (RI) and stiffness index (SI) of young subjects and those of aged participants with or without diabetes. By comparing the RI and SI measured by an air pressure sensing system in patients with well and poorly controlled diabetes, the authors demonstrated that these parameters may serve as potential indicators for monitoring the progression of atherosclerosis and endothelial dysfunction in elderly diabetic subjects. Liang et al.[35] used EMD to discuss artefact reduction in order to increase the quality of electrogastrogram (EGG) recordings. This method, combined with IF analysis, can effectively separate, identify, and remove contamination from a wide variety of artifactual sources in EGG recordings. Chappell and Payne[36] developed an EMD-based method of detecting venous gas bubbles, and used the EMD to calculate the IMFs of a number of Doppler ultrasound signals from recreational divers. They obtained the deviations in the ensemble average of the IMF in each heart cycle to extract the features, and bubbles were detected in the IMFs with the correct energy characteristics. This method offers a significant improvement over the current aural assessment technique for the detection of bubbles associated with decompression sickness (DCS). Peng et al.[37] used the HHT method to analyse the electromyographic signal (sEMG) characteristics of muscular fatigue. They found that the energy approximately increases and the instantaneous frequency decreases during the entire fatiguing process. Speech signals have also been analysed by HHT-based methods. Yang et al.[38] developed an HHT-based pitch period detection algorithm and used it to locate the instant at which the glottal pulse occurs. The authors computed the derivative of instantaneous energy (DIE), defined a threshold, and searched for the local maxima of the DIE. The instants at which the local maxima of the DIE occurred corresponded to those at which the glottal pulse occurred, and the pitch period was detected by measuring the time interval between two glottal pulses. Huang and Pan[39] used HHT to determine the speech pitch in order to improve the accuracy and resolution of pitch recognition.

Data truncation and separation into frames are no longer necessary and the time-varying characteristics of speech signals can be represented directly. The method can show rapid pitch variations between each pitch period. Li et al. [40] developed an EMD signal reconstruction method based on the Teager energy operator (TEO) in order to examine speech emotion recognition. Speech emotion states such as anger, boredom, disgust, fear, happiness, neutral, or sadness were identified with a recognition rate of 81.43%. '○' denotes the analysis technology used in previous studies and the HHT method. From Table 3, we see that IMF technology was used by Liao et al.,[33] Wu et al.,[34] Liang et al.,[35] Chappel and Payne,[36] Peng et al.,[37] Yang et al.[38] Huang and Pan,[39] and Li et al.[40] The RI and SI technologies were applied by Wu et al.[34]; EEMD technology was adopted by Liao et al.[33] and Wu et al.,[34]; Chappell and Payne[36] and Peng et al.[37] employed energy characteristics; TEO technology was used by Li et al.[40]; EMD technology was used by Liao et al.,[33] Liang et al.,[35] Chappell and Payne,[36] Yang et al.,[38] Huang and Pan,[39] and Li et al.[40]; a DIE scheme is adopted by Yang et al.,[38]; IFs scheme was employed by Liang et al.,[35] Peng et al.,[37] and Huang and Pan[39]; threshold scheme was used by Yang et al.[38] Using these studies, we can examine the following methods that are commonly used to obtain and determine voice, EGG, and other medical signal features analysis: HHT frequency analysis integrated with the IMFs, RI, SI, EEMD, TEO, EMD, DIE, IFs, threshold.

Discussion

The commonly discussed ζ, δ, θ, α, β, and γ bands of brain wave frequency ranges comprise frequencies of more than 0 to 0.5 Hz, 0.5 to 4 Hz, 4 to 8 Hz, 8 to 12 Hz, 12 to 30 Hz, and above 30 Hz, respectively. The frequency range commonly recorded by an ECG is 0 to 80 Hz. The frequency energy distributions of other biomedical signals vary according to the biomedical signal media and related symptoms of interest. Conventional analysis methods primarily use Fourier spectral analysis to determine the frequency energy distribution of biomedical signal media. With the development of wavelet transform analysis, we can analyse the time-frequency energy distribution of each biomedical signal media. However, the wavelet transform analysis media has worse time-energy distribution resolution. Comparatively, the HHT analysis method provides a better resolution for the time-frequency-energy distribution. The use of HHT analysis combined with statistics or other methods was discussed in the previous sections. From these examples, we can better understand the resolution and use of the time-frequency-energy distribution characteristics of biomedical signal media. These characteristics cannot be resolved or precisely detected using the Fourier or wavelet transform methods. Therefore, HHT enables us to better

Table 3. HHT-based analysis methods and the system features of other medical signal applications.

	Applications	IMFs	RI	SI	EEMD	Energy characteristics	TEO	EMD	DIE	IFs	Threshold
Liao et al.[33]	Improve the CTR of PI-based ultrasound non-linear imaging	○			○			○			
Wu et al.[34]	Radial arterial waveform analysis and EEMD diabetic control in the elderly	○	○	○	○						
Liang et al.[35]	Artefact reduction in order to increase the quality of EGG recordings	○						○		○	
Chappell et al.[36]	Detecting venous gas bubbles	○				○		○			
Peng et al.[37]	The sEMG characteristics of muscular fatigue	○				○				○	
Yang et al.[38]	An HHT-based pitch period detection algorithm	○						○	○		○
Huang et al.[39]	Determine the speech pitch in order to improve the accuracy and resolution of pitch recognition	○						○		○	
Li et al.[40]	Examine speech emotion recognition	○					○	○			

Note: for abbreviation definitions, please see Appendix 1.

understand the differences between the frequency characteristics of biomedical signal media for normal and abnormal symptoms of diseases. This enables physicians to provide more precise disease prevention, detection, diagnosis, and treatment.

Conclusions

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, PI based non-linear ultrasound imaging, diastolic peak detection, EGG signals, venous gas bubble detection, EMG characteristics of muscular fatigue, speech pitch period detection, and speech emotion recognition. From these examples, we can see how the HHT time-frequency analysis is used to detect, analyse, and process, biomedical signals and develop new approaches to diagnosing or monitoring various illnesses. This study examines the application of HHT integrated with numerous methods for analysing biomedical signal frequency characteristics. Future studies can further develop and examine more HHT frequency characteristic analysis methods. This research team aims to continue exploring the signal frequency characteristics of spike waves, sharp waves II, sharp waves III, alcoholism FP2 channel and FZ brain wave channel, and voice rehabilitation, to enable greater understanding of the HHT frequency characteristics of these signals.

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Appendix

Abbreviations

BCI	brain–computer interface
BER	bit error rate
CTR	contrast-to-tissue ratio
DCS	decompression sickness
DIE	derivative of instantaneous energy
EMD	empirical mode decomposition
ECG	electrocardiogram
EEG	electroencephalogram
EGG	electrogastrogram
EMG	electromyographic
EEMD	ensemble EMD
FIR	finite impulse response
FBRIR	frequency band relative intensity ratio
GT	Gabor transform
GPGPU	general-purpose computing on a graphics processing unit
HT	Hilbert transforms
HHT	Hilbert–Huang transformation
HHS	Hilbert–Huang spectrum
HMF	Hilbert-marginal frequency
HHSE	Hilbert–Huang spectral entropy
HHES	Hilbert–Huang energy spectra
HS	Hilbert spectral
IMF	intrinsic mode function
IF	instantaneous frequency
MMCDI	maximum Manhattan and Canberra distances of the IMFs
PI	pulse-inversion
PS	phase statistics
RI	reflection index
REM	rapid eye movement
SI	stiffness index
SC	statistical characteristics
SS	sleep spindle
SNR	signal-to-noise ratio
TFED	time-frequency-energy distributions
TEO	Teager energy operator
VF	ventricular fibrillation