

# Chapter 94

## Investigation Performance on Electrocardiogram Signal Processing based on an Advanced Algorithm Combining Wavelet Packet Transform (WPT) and Hilbert-Huang Transform (HHT)\*

Jin Bo, Xuewen Cao, Yuqing Wan, Yuanyu Yu, Pun Sio Hang, Peng  
Un Mak and Mang I Vai

**Abstract** The Electrocardiogram (ECG) is essential for the clinical diagnosis of cardiovascular disease. An advanced algorithm combining wavelet packet transformation (WPT) and Hilbert Huang transform (HHT) is presented for processing ECG (Electrocardiography) signal in this paper. First the WPT can resolve the ECG signal into a group of signals with narrow band. Then, the Empirical Mode Decomposition (EMD) process of Hilbert-Huang Transform (HHT) is applied on the narrow band signals. The unrelated IMFs of ECG signal are removed from result through a screening process. Finally, the Hilbert transform is employed to achieve the Hilbert spectrum and marginal spectrum. The results show the

---

The work was financially supported by The Science and Technology Development Fund of Macau under Grant 014/2007/A1, Grant 063/2009/A, and Grant 024/2009/A1, the National Natural Science Foundation of China under Grant 61201397 and University of Macau RG069/07-08S/MPU/FST.

---

J. Bo (✉) · X. Cao · Y. Yu · P. S. Hang · P. U. Mak · M. IVai  
Department of Electrical and Computer Engineering, Faculty of Science and Technology,  
University of Macau, Taipa, Macau  
e-mail: gfkbsncz@gmail.com

Y. Wan  
Department of Computer and Information Science, Faculty of Science and Technology,  
University of Macau, Taipa, Macau

P. S. Hang · M. IVai  
State Key Laboratory of Analog and Mixed-Signal VLSI, University of Macau, Taipa,  
Macau

effective performance of the algorithm combining WPT and HHT in reducing ECG noise and time–frequency analysis. By comparing with the original HHT, the proposed algorithm has the better performance on ECG signal processing.

**Keywords** ECG · WPT · EMD · HHT

## 94.1 Introduction

The Electrocardiogram (ECG) is a typical case of biomedical signal and can interpret the electrical activities over a period of time. The Electrocardiogram (ECG) detected and recorded by surface electrodes is essential for the clinical diagnosis of cardiovascular disease. Time series data sampled from biomedical signals are often considered linear and stationary arising from physical processes. But biomedical signals are considered nonlinear and nonstationary when signals are related to dynamic biological system. Due to nonlinear and nonstationary property of ECG signals, an adaptive processing method is required.

Time–frequency analysis is to describe a signal energy density in time and frequency domains simultaneously [1]. There are several common time–frequency analytic techniques such as Gabor-Wigner Transform, Wigner Distribution Function (WDF), Short-time Fourier Transform (STFT) and Wavelet Transform (WT). The Hilbert-Huang Transform (HHT) developed by Huang et al. is a new method to extract the features of nonlinear and nonstationary signals [2] and it is widely used in many fields. But in practical applications HHT has many deficiencies [3, 4]: First, IMFs undesired at the low-frequency section produced by EMD lead misinterpretation to the result easily. Second, depending on the analysed signal, the monocomponent property cannot be satisfied when the 1st IMF frequency range may be too wide. Third, signals containing low-energy components cannot be separated through the EMD operation.

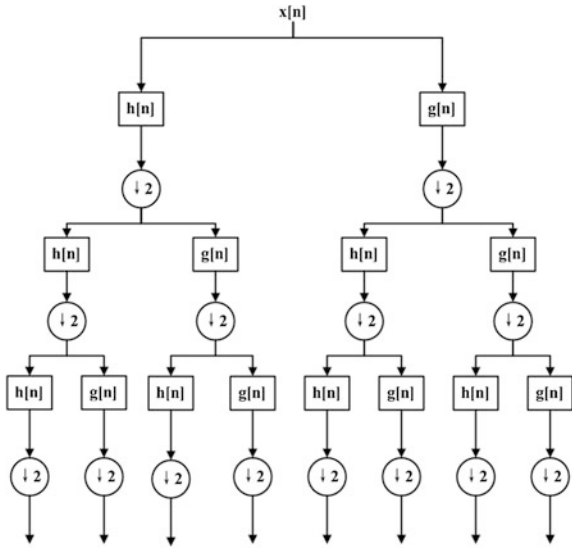
In this paper, an advanced analysis method combining wavelet packet transform (WPT) and Hilbert-Huang transform (HHT) is applied on ECG signal. With this method, the deficiency of HHT can be solved to some extent.

## 94.2 Principle

### 94.2.1 Wavelet Packet Transform

Wavelet packet transform (WPT) is an extended multi-resolution signal processing method of wavelet transform (WT). The detail and approximation coefficients can be decomposed to create the full binary tree through WPT. More filters for input

**Fig. 94.1** The wavelet packet decomposition process



signal are needed to pass in WPT method than in the wavelet transform. Thus WPT can provide better local complete time–frequency analysis. The wavelet packet decomposition process can be shown as Fig. 94.1.  $2n$  different sets of coefficients can be produced through WPT process and the signal can be decomposed into  $2n$  narrow bands for  $n$ -level of decomposition [5].

The wavelet packet functions are defined through  $\mu_0, \mu_1, h, g$  as Eq. (94.1):

$$\begin{cases} \mu_{2n}(t) = \sum_{k \in \mathbb{Z}} h_k \mu_0(2t-k) \\ \mu_{2n+1}(t) = \sum_{k \in \mathbb{Z}} g_k \mu_0(2t-k) \end{cases} \quad (94.1)$$

Where  $\{\mu_n(t)\}_{n \in \mathbb{Z}}$  are the orthogonal wavelet packets,  $h_k$  are low-pass filter coefficients,  $g_k$  are high-pass filter coefficients. When  $n = 0$ , the functions denote the scaling function:  $\mu_0(t) = \phi(t)$  and wavelet function:  $\mu_1(t) = \varphi(t)$

### 94.2.2 Hilbert-Huang Transform

Empirical mode decomposition (EMD) and Hilbert spectral analysis (HSA) these two approaches comprise the Hilbert-Huang transform (HHT) [2] which is a development method for processing nonstationary and nonlinear signals.

The first procedure of HHT is EMD which can decompose a signal to a series of intrinsic mode function (IMF) which needs to fulfill two constraints [2]. In EMD process, assume  $x(t)$  represents a non-linear and non-stationary input signal. Curve fitting technique is applied to achieve the upper and lower envelopes of the input

signal. The difference between input signal  $x(t)$  and the mean value of the upper and lower envelopes of input signal  $x(t)$  is calculated repeatedly until the sifted signal satisfies IMF condition. The same procedure is applied to the residual result again and again until the residual is a mean trend or constant. The final result of EMD through above procedures indicates input signal  $x(t)$  consists of a series of IMF ( $c_i$ ) and a remainder ( $r_n$ ), a constant or mean trend, which can be represented as Eq. (94.2).

$$x(t) = \sum_{i=1}^n c_i + r_n \tag{94.2}$$

The second procedure of HHT is Hilbert spectrum analysis. The input signal can be expressed as Eq. (94.3) in which  $a_j(t)$  is instantaneous amplitude corresponding to  $j$  th IMF and  $\omega_j(t)$  is instantaneous frequency corresponding to  $j$  th IMF after performing the Hilbert transform (HT) on each IMF:

$$x(t) \sum_{j=1}^n a_j(t) \exp\left(i \int \omega_j(t) dt\right) \tag{94.3}$$

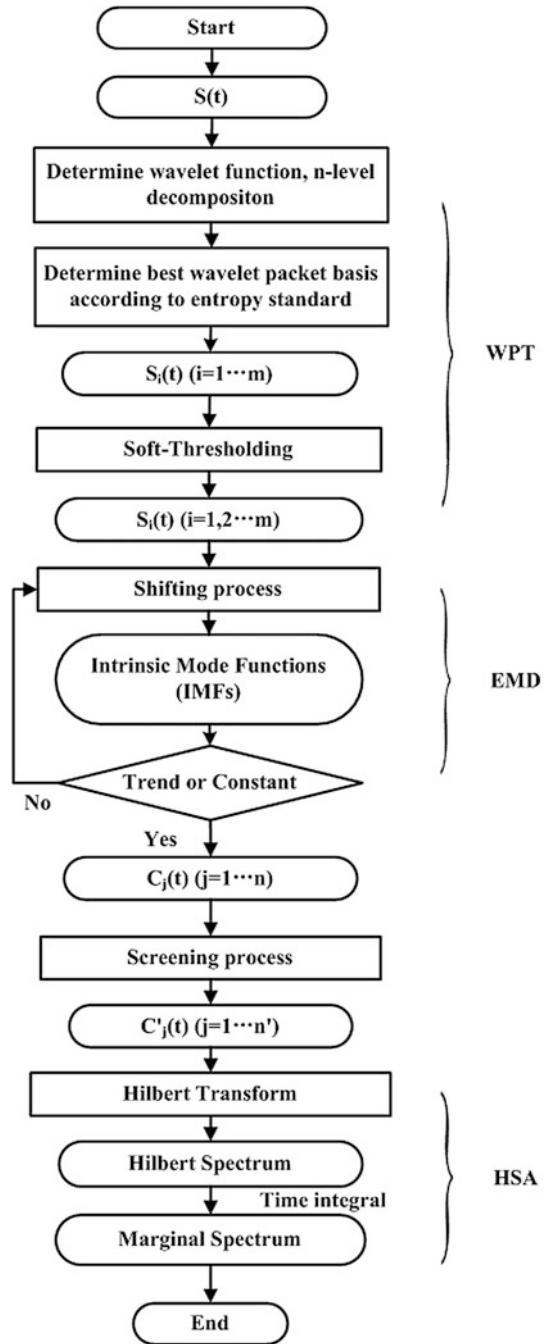
Equation (94.3) can indicate that one signal can be represented in three-dimension by its instantaneous amplitude  $a_j(t)$  and instantaneous frequency  $\omega_j(t)$  as a function of time  $t$ . The marginal spectrum  $h(\omega)$  which indicates the contribution of energy on each frequency value is defined as Eq. (94.4) in which the Hilbert spectrum  $H(\omega, t)$  replacing  $x(t)$  is considered as time–frequency distribution of amplitude:

$$h(\omega) = \int_0^T H(\omega, t) dt \tag{94.4}$$

### 94.2.3 Combining WPT and HHT

In the algorithm combining WPT and HHT, the ECG signal is separated into a set of narrow band signals through the WPT process in which Soft-Thresholding method [6] is selected firstly. Second, the EMD process of HHT is applied on the narrow band signals. Screening procedure is applied to remove IMFs which is unrelated. Last, the HT is utilized to achieve the Hilbert spectrum and marginal spectrum. The flow chart of the algorithm combining WPT and HHT is shown as Fig. 94.2.

**Fig. 94.2** The flow chart of the algorithm combining WPT and HHT

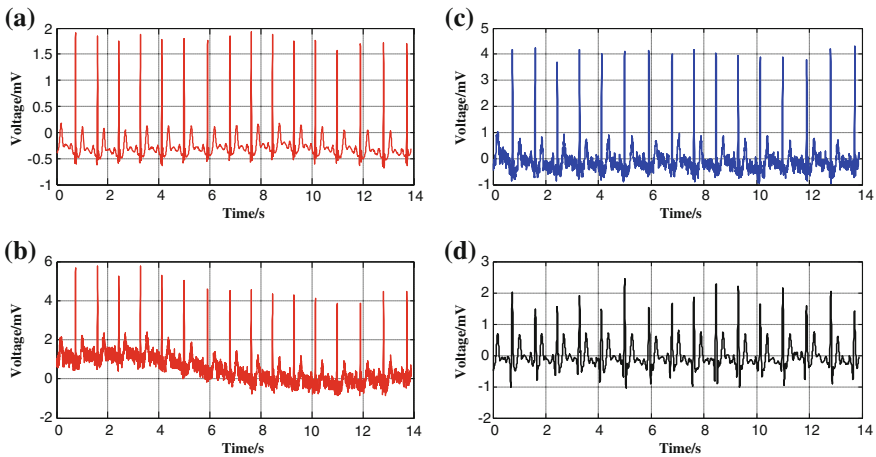


### 94.3 Application on ECG

The recording of Electrocardiogram (ECG) is vital for the clinical diagnosis of cardiovascular disease. But ECG signal which frequency range is from  $0 \sim 100$  Hz is very weak compared with the interference noise including Electromyography (EMG) signal interference which frequency range is 2–5 Hz, power line interference which frequency is 50 Hz, movement artifact which frequency range is below 7 Hz and baseline wander which frequency range is 0.15–0.3 Hz. Denoising is essential for extract features for clinical diagnosis.

#### 94.3.1 Simulated ECG Denoising

For investigating the performance of the algorithm, the ECG signal from MIT-BIH standard database (see Fig. 94.3a) adding simulated white noise (SNR 15 dB), power line interference simulated a cosine function of 50 Hz and baseline wander simulated by a function of combining cosine function and sine function is used. As mentioned above, WPT process is prior to HHT. The Bior 5.5 wavelet, 3-level decomposition is selected. The HHT algorithm is also applied comparing with the WPT and HHT combination algorithm. The result is shown as Fig. 94.3. From Fig. 94.3c and d, no matter white noise, power line interference and baseline wander are reduced in both method but more noise is retained in through HHT method alone than through WPT and HHT. And significant information in original waveform is also retained by proposed method.



**Fig. 94.3** **a** The clear ECG signal and the ECG signal with simulated noise; **c** the denoised ECG signal with HHT; **d** the denoised ECG signal with WPT and HHT

**Table 94.1** Parameters for Denoise Performance

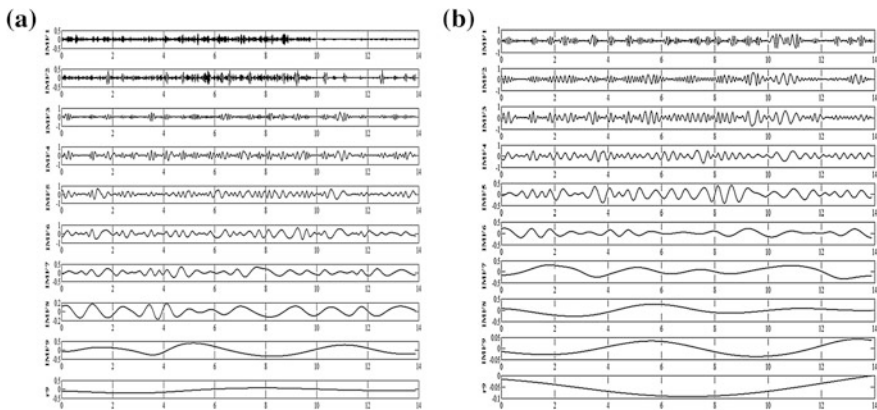
Signal	SNR	MSE	Correlation coefficient
$x_1(t)$	5 dB	2.83e-4	0.620
$x'_1(t)$	12.4 dB	3.25e-5	0.872
$x_2(t)$	10 dB	2.37e-4	0.690
$x'_2(t)$	16.8 dB	3.51e-5	0.916
$x_3(t)$	15 dB	2.25e-4	0.722
$x'_3(t)$	21.5 dB	2.99e-5	0.923

$x(t)$  is signal before denoising,  $x'(t)$  is signal after denoising

By using simulated noisy signal, the performance of the algorithm of combining WPT and HHT is investigated. The result shown as Table 94.1 indicates the proposed algorithm is effective. SNR and Correlation Coefficient increase obviously while MSE decreases after denoising. Furthermore, practical ECG data is applied.

### 94.3.2 Real ECG Analysis

Data of ECG signal used is from MIT-BIH standard database. From MIT-BIH databases header file, we know that data file of 203.dat includes considerable noise including muscle artifact and baseline shifts. The EMD result with WPT preprocessing and without WPT preprocessing and is shown as Fig. 94.4. IMF1 and IMF2 which cannot satisfy monocomponent definition very well in Fig. 94.4a contain high frequency components obviously, while IMF1 and IMF2 in Fig. 94.4b do not have, which is because that WPT process can denoise and retain the low-energy component. Thus the EMD efficiency increases by WPT preprocessing.

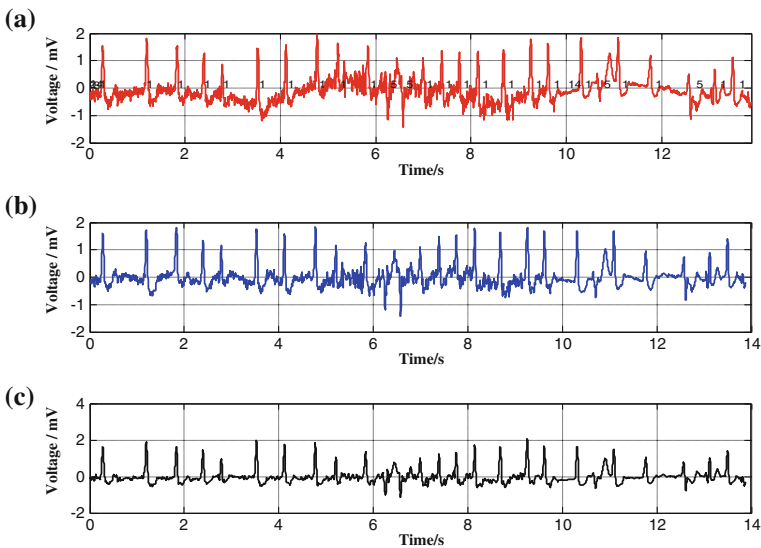


**Fig. 94.4** The EMD result for (a) the algorithm without WPT (b) the algorithm with WPT

Before reconstruct the signal, a screening process through calculating correlation coefficient is applied after EMD process to remove the low frequency IMF and unrelated component. The results of denoising with WPT and without WPT are shown in Fig. 94.5. From Fig. 94.5a and b both two algorithms have denoise function, but HHT performs not well. The algorithm combining WPT and HHT not only can denoise well but also retain the specific waveform significant annotated in original waveform. The conclusion from Fig. 94.5 is that the algorithm combining WPT and HHT is more effective and better than HHT, which is consistent with simulated result.

The FFT spectrum of the original signal of 203.dat and the marginal spectrum which is through the proposed method are shown in Fig. 94.6. In Fig. 94.6a, FFT spectrum shows the energy mainly below 20 Hz of the ECG signal is disperse, which is affected by the noise. While in Fig. 94.6b the marginal spectrum shows the concentration of energy. The energy is more concentrate on the low frequency section, which is not only because noise reduction of the proposed algorithm and indicates the effectivity of the proposed algorithm but also because marginal spectrum represents the accumulation of amplitude corresponding to instantaneous frequency, which is different with definition of Fourier transform.

Equation (94.3) can represent the instantaneous amplitude, instantaneous frequency and time as a contour map. The distribution of amplitude of Hilbert-Huang spectrum is shown as Fig. 94.7 which is of 203.dat. In Fig. 94.7, though the main energy is concentrate on the low frequency section, the frequency of ECG signal



**Fig. 94.5** Results of denoising. The original signal of 203.dat is in red line (a). The denoised ECG signal with HHT is in blue line (b). The denoised ECG signal with WPT and HHT is in black line (c)



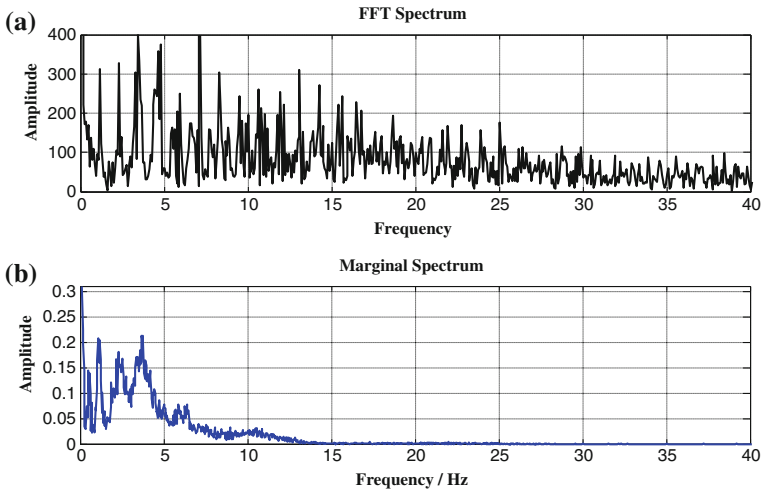


Fig. 94.6 a The FFT spectrum of the original ECG signal and b The marginal spectrum

varies in an abnormal range as time flows in Hilbert-Huang spectrum, which is an arrhythmia phenomenon that can be proved through transforming R-R interval signal to HRV signal to perform proposed method. The Hilbert-Huang Spectrum by proposed method can indicate the resolution is uniform for overall frequency part and reveal the instantaneous phenomenon in Fig. 94.7. The reason is that in proposed method the concept of time resolution and frequency resolution is not used, while the concept of instantaneous frequency is applied.

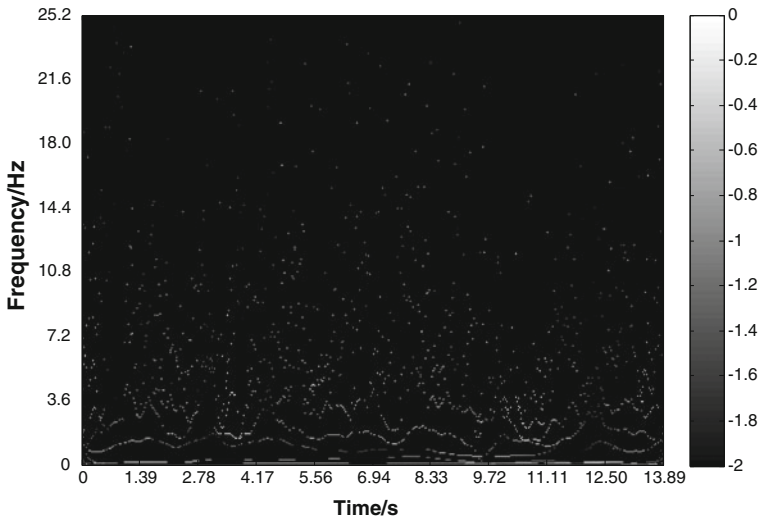


Fig. 94.7 The Hilbert-Huang Spectrum

## 94.4 Conclusion

In this paper, we have investigated the performance on ECG signal processing based on an advanced algorithm combining WPT and HHT. The result of application on ECG processing indicates the proposed method enhances the EMD efficiency and is effective on denoising ECG. In addition, the marginal spectrum of the proposed method can show the exact energy contribution corresponding to instantaneous frequency and Hilbert-Huang spectrum of the proposed method can provide clear uniform resolution and time–frequency distribution for extract features.

## References

1. Cohen L (1995) Time-frequency analysis. Prentice Hall, New Jersey, p 299
2. Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, Yen NC, Tung CC, Liu HH (1998) The empirical mode decomposition and Hilbert spectrum for nonlinear and nonstationary time series analysis. *Proc R Soc London* V454:903–995
3. Peng Z, Tse P, Chu F (2005) A comparison study of improved Hilbert–Huang transform and wavelet transform: application to fault diagnosis for rolling bearing. *Mech Syst Signal Process* 19:974–988
4. Peng ZK, Tse PW, Chu FL (2005) An improved Hilbert–Huang transform and its application in vibration signal analysis. *J Sound Vib* 286:187–205
5. Dequeiroz RL, Rao KR (1993) Time-varying lapped transforms and wavelet packets. *IEEE Trans Signal Process* 41:3293–3305
6. Donoho DL (1995) De-noising by soft-thresholding. *IEEE Trans Inf Theory* 41(3):613
7. Huang NE, Shen SSP (2005) Hilbert-huang transform and its applications. *Interdiscip Math Sci* 5:1–26
8. Rilling G, Flandrin P, Goncalves P (2003) On empirical mode decomposition and its algorithms. In: *Proceedings IEEE-EURASIP workshop on nonlinear signal and image processing, Grado (I)*
9. Flandrin P, Rilling G, Gonçalves P (2004) Empirical mode decomposition as a filterbank. *IEEE Signal Proc Lett* 11:112–114
10. Kopsinis Y, McLaughlin S (2008) Empirical mode decomposition based soft-thresholding. In: *Proceedings 16th European signal processing conference (EUSIPCO), Lausanne, Switzerland, 25–29 Aug 2008, Available:CD-ROM*
11. Kopsinis Y, McLaughlin S, Empirical mode decomposition based denoising techniques. In: *Proceedings 1st IAPR workshop cognitive information processing (CIP), Santorini, Greece, 9–10 Jun 2008, pp 42–47*