ANALYSIS OF HEART RATE VARIABILITY SIGNALS USING HILBERT-HUANG TRANSFORM

Marwa Obayya [1] and Fatma Abou-Chadi [2]

[1] Deptartment of Electronics and Communications Engineering, Mansoura University
marwa_obayya @yahoo.com.

[2] Head of Deptartment of Electronics and Communications Engineering, Mansoura University
f-abochadi@ieee.org

ABSTRACT

In this paper, an attempt was made to utilize the Hilbert-Huang transform (HHT) for the analysis of heart rate variability signals in order to discriminate between normal subjects and patients with low heart rate such as those who suffering from congestive heart failure (CHF) and myocardial infarction (MI). This decomposition method is adaptive and therefore highly efficient. Using the Empirical mode decomposition (EMD) method, HRV signals are decomposed into a finite and often small number of intrinsic mode functions (IMFs) that admit well-behaved Hilbert transforms. The final presentation of the results is an energy-frequency-time distribution, known as the Hilbert spectrum. Then the features were statistically analysed by analysis of variance (ANOVA) test. It has been shown that the use of HHT may prove to be a vital technique for the analysis of heart rate variability signals.

Keywords: *Empirical mode decomposition (EMD), intrinsic mode functions (IMFs), analysis of variance (ANOVA), and Hilbert spectrum.*

1. INTRODUCTION

Heart Rate Variability (HRV) is increasingly used to assess autonomic dysfunction in different pathological conditions, either of cardiac (myocardial infarction, congestive heart failure, life threatening arrhythmias), or noncardiac origin (diabetes, neuropathies, obesity, etc [1].

From clinical view, a high degree of heart rate (HR) variability is found in persons with normal hearts, whereas low HR variability can be found in patients with congestive heart failure and patients after myocardial infarction [2]-[4]. Lombardi and Mortara [4] has been clarified that the possibility of using HRV as a prognostic indicator in patients with cardiac failure as well as post myocardial infarction patients, stems directly from the compelling evidence that has been accumulated over the past few years about the importance of the derangement of autonomic nervous control of the cardiovascular system as one of the mechanisms involved in the occurrence of cardiac-particularly sudden-death. Also, they review some of the most interesting and recent results obtained with the analysis of HRV in patients with cardiac failure, focusing on two principal aspects; the detection of an abnormal autonomic modulation of sinus node, and the prognostic value of reduced HRV [4].

Reported approaches to characterizing HRV include elementary statistical measures of the properties of the R-R intervals [2], spectral analysis of heart rate or R-R interval time series [5]-[10]. However, these methods are limited by implicit assumptions of linearity and stationarity [11]-[13]. Moreover, spectral estimation inherently assumes that the signal is at least weakly stationary. However, real HRV is a non-linear signal and is usually nonstationary. Nonlinearities can be dealt through the determination of the nonlinear parameters as described in [14]. However, nonstationarities like slow linear or more complex trends in the HRV signal, can cause distortion to time-and frequency-domain analysis [15].

To deal with nonlinear and non-stationary signals, Huang et al. [16] proposed a technique called Hilbert-Huang transform (HHT). The technique is based on the direct extraction of the energy associated with various intrinsic time scales. The local energy and the instantaneous frequency derived from the IMFs through the Hilbert transform can give a full energy-frequency-time distribution of the data. Such a representation is designated as the Hilbert-spectrum [16].

In this paper, we introduce the use of the basis function of the Hilbert-Huang transform as features to be used as discriminant parameters between patients with high and low heart rate. This achieved by applying Hilbert-Huang transform to a set of real HRV short-term data obtained from normal subjects and patients suffering from congestive heart failure and myocardial infarction diseases

The paper is organized as: Section-2 presents overview of HRV data collection. Section -3 presents the empirical mode decomposition (EMD), HHT; and the time-frequency representation. Section-4 includes the HHT feature extraction. Section–5. provides ANOVA test for HHT features. While section – 6 is the conclusion.

2. DATA COLLECTION

The input signal to EMD is the RR database obtained from the PhysioBank Interbeat (RR) Interval Databases extracted from website of RR database [17]. Three groups were chosen which are Normal Sinus Rhythm (NSR), Congestive heart failure (CHF), Myocardial Infarction pre-medication (MI). For normal sinus rhythm, 72 beat annotation files for long-term ECG recordings (35 men, aged 26 to 76, and 37 women, aged 20 to 73) were used. For congestive hear failure, 48 beat annotation files for

long-term ECG recordings of subjects aged 22 to 79. Subjects included 19 men and 6 women; gender is not known for the remaining 23 subjects. For myocardial infarction, 100 beat annotation files for long-term ECG recordings of patients with myocardial infraction pre-medication. Gender is not defined for this database. We perform EMD method on heart rate variability signals of length 1024 samples (8 seconds where sampling rate is 128 sample/second).

3. EMPIRICAL MODE DECOMPOSITION

The empirical mode decomposition (EMD) was first introduced by Huang et al [16], which is the basis functions of the so-called Hilbert- Huang Transform (HHT). The empirical mode decomposition (EMD) method is composed of a three step algorithm. First data 'sifting' to generate the intrinsic modes (IMF), second step is to apply the Hilbert transform to the intrinsic modes and the third step performs a spectral analysis using the Hilbert Transform using the IMF amplitudes and instantaneous frequencies.

3.1 IMF COMPUTATION

The principle of EMD is to decompose a signal into a sum of oscillatory functions, namely intrinsic mode functions (IMFs), that: 1) have the same numbers of extrema and zero-crossings or differ at most by one; and 2) are symmetric with respect to local zero mean [18]. An iterative algorithm called the sifting technique computes the IMFs. Let *x (k); k = 1,…, k* be the original signal. The sifting evolves according to the following steps:

a. Find the all maxima and minima of x (k).

b. Compute the corresponding interpolating signals $x_{up}(k)$ and $x_{low}(k)$ with cubic spline interpolation.

c. Calculate the point-by-point mean from the upper and lower envelopes, $m(k)=[x_{up}(k)+x_{low}(k)]/2$.

d. Extract the details; d (k) =x (k)-m (k).

e. Check the properties of d(k):

- If d (k) meets the above defined two conditions, an IMF is derived; $IMF_1(k)=d(k)$ and replace x (k) with the residual r (k) =x (k)-IMF (k).
- If d (k) is not an IMF, replace x (k) with d (k).

f. Repeat steps from (a) to (e) until the residual satisfies some stopping criterion.

To guarantee that the IMF components retain enough physical sense of both amplitude and frequency modulation, Huang et al [16] gave a criterion for the sifting process to stop. This can be accomplished by limiting the size of the normalized standard deviation, *SD*, computed from two consecutive sifting results as

$$SD=\sum_{k=1}^{K}\frac{\left|x_i(k)-x_{i+1}(k)\right|^2}{\left|x_i(k)\right|^2} \qquad (1)$$

The normalized *SD* is usually set between 0.2 and 0.3. Finally, x (k) can be expressed as f follows:

$$x(k)=\sum_{i=1}^{M} IMF_i(k)+r_M(k) \qquad (2)$$

Where M is the number of IMFs, $r_M(k)$ denotes the final residue which can be interpreted as the dc component or the trend of the original signal, and $IMF_i(k)$ are nearly orthogonal to each other, and have nearly zero means. Due to this iterative procedure, none of the sifted IMFs is derived in closed analytical form [19].

Fig.1 shows the total number of IMFs extracted from heart rate variability signal of a normal subject.

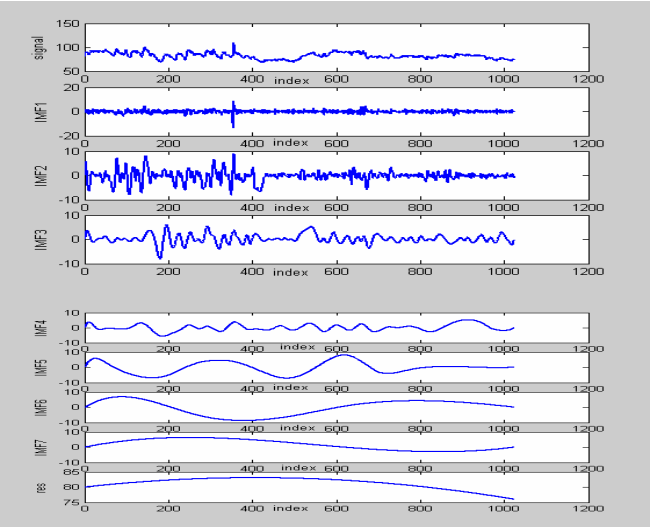

Figure 1: Seven IMFs extracted from heart rate variability signal of a normal subject.

3.2 IDENTIFICATION OF TREND

By the nature of the decomposition procedure, the data is decomposed into M fundamental components, each with distinct time scale. More specifically, the first component as the smallest time scale which corresponds to the fastest time variation of data. As the decomposition process proceeds, the time scale increases, and hence, the mean frequency of the mode decreases. Based on this observation a general time space filtering may be of the form:

$$y(k)=\sum_{i=l}^{h} IMF_i(k) \qquad (3)$$

Where y (k) is the filter output, and *l, h* $\in[l,\ldots,N]$, $1\le h$; if l=1, and h<N, it is a high pass , if l > 1, and h = N, it is a

low pass filter, if $1 \prec l \le h \prec N$, it is a band pass filter. A three-step procedure to identify the slow-varying trend: 1) the mean and the standard deviation of y (k) taken over time are performed as a function of h; 2) one-sample t-test is used to determine when the mean significantly departs from zero; and 3) once h is identified partial reconstruction is done; with a final residual composed of the resulting IMFs from *h+1* to *N*.

To quantify the performance of EMD method, the root-mean squared error (RMSE) is used as the error measure:

$$RMSE = \sqrt{\sum_{k=1}^{K} (y(k) - x(k))^2 / K} \qquad (4)$$

Where *K* is the number of time points; Fig. 2 shows the step-by-step coarse-to-fine reconstruction of the HRV signal for normal subject from the IMF components where the original signal is plotted in blue lines and partial sum of the IMFs in green lines. The very first plot shows the signal and the last component IMF8, the residue of the sifting, which denotes the dc component in the original signal. The very last plot shows the summation of all the IMFs, which looks like the original data with RMSE equal to 1.3874e-014. The intermediate plots show the progress of addition of the IMF components. If we stopped at any step, the data was filtered.

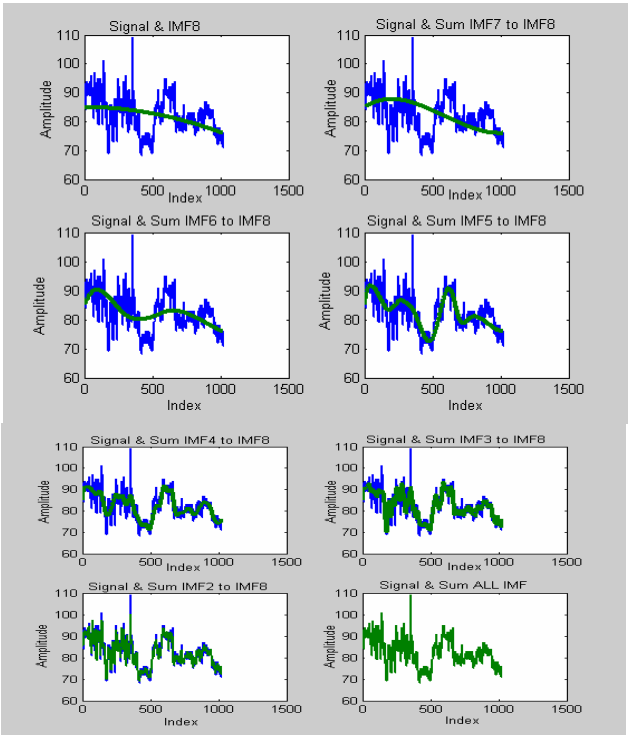

Figure 2: Illustration of the EMD acting as a low-pass filter through the reconstruction of the data from the IMF components

3.3 DISCRETE HILBERT TRANSFORM

The Hilbert transform was first developed to process non-stationary narrow-band signal [20]. The Hilbert transform is a time series analysis technique to derive amplitude and phase information of a data set as a function of time.

The discrete Hilbert transform (DHT) of N-point's signal *x (k)* is calculated as follow:

a. Calculate the Discrete Fourier Transform (DFT) of the signal x (k); $X_1 = DFT\{x(k)\}$.

b. Compute the Hilbert transformer operator *H(k)*

$$H(k) = \begin{cases} 1 & \text{for k = 1, N/2 + 1} \\ 2 & \text{for k = 2,3,..., N/2} \\ 0 & \text{for k = N/2 + 2,..., N} \end{cases} \qquad (5)$$

c. Calculate the element wise product; Y=H. X_1.

d. Calculate the inverse DFT of the product; y=IDFT{Y (k)}, then the DHT is H{x(k)} =Real{y (k)}.

Given a real signal x(k) , one can build the corresponding analytic signal (or complex trace) [21] :

$$X(k) = x(k) + j.H\{x(k)\} = A(k)e^{j.\theta(k)} \qquad (6)$$

Where

$$A(k) = \sqrt{[x(k)]^2 + [H\{x(k)\}]^2}\ , \theta(k) = \arctan\left(\frac{H\{x(k)\}}{x(k)}\right) \quad (7).$$

Huang et al proposed the instantaneous frequency

$$\omega(k) = \theta(k) - \theta(k-1); \qquad k = 2,3,...,N \qquad (8)$$

Fig.3 shows the original HRV signals (solid line) of a normal subject and its Hilbert –Transform (dotted line). It can be noted from the figures that the Hilbert transform is related to the original signal by a 90° phase shift.

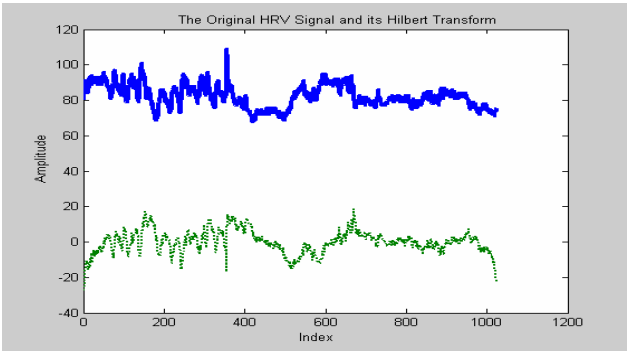

Figure 3: The Hilbert transform of the original HRV signal for (a) normal sinus rhythm

3.4. HILBERT AMPLITUDE SPECTRUM

Hilbert amplitude spectrum of the initial time series can be represented as in Huang et al.[16], which is obtained in the following way: for each intrinsic mode function $IMF_i(k)$, if $\omega_i(k)$ is the corresponding instantaneous function, one can represent in three dimension plot the triplet {k , $\omega_i(k), A_i(k)$} where $A_i(k)$ is the amplitude of the complex trace associated to $IMF_i(k)$. Fig.4 (a) shows the Hilbert –Huang amplitude spectrum for each IMFs for a normal subject

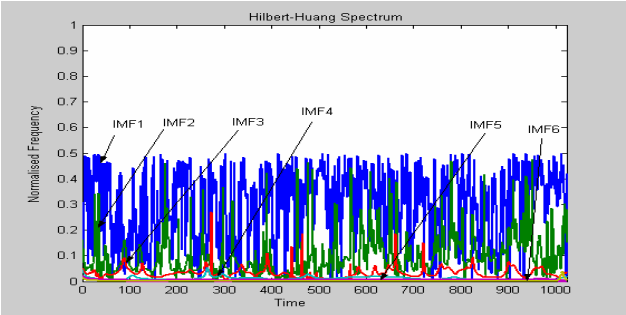

Figure 4.: The Hilbert –Huang Spectrum for each IMFs for a normal subject

4. HILBERT-HUANG TRANSFORM FEATURE EXTRACTION

Hilbert-Huang transform was performed on segments of length 1024 samples of the HRV signals for the different three groups. For each subject's heart rate time series, a sequence of amplitudes describing the time dependent magnitude of the intrinsic mode functions IMFs was obtained. Then the energy content [22] of each IMFs amplitude obtained by the Hilbert transform for each subject was calculated.

5. STATISTICAL ANALYSIS OF FEATURES

In this section, Hilbert-Huang transform features have been analyzed by means of variance (ANOVA) for repeated measures [23]. When the factor was significant ($p \prec 0.05$), we further checked the significance of the differences between normal subjects and patients suffering from CHF and MI diseases. Results of ANOVA are shown as means $\pm$ standard deviation in Fig. (5), Table -1.

It has been found that only four coefficients from six are significant. Therefore, it is concluded that HHT able to discriminate between the three groups under investigation at 5% level of significance.

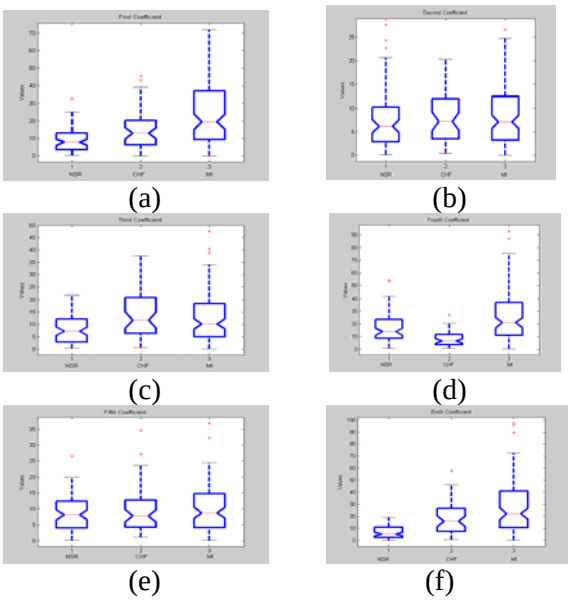

Figure 5: ANOVA results for features of Hilbert-Huang transform in normal subjects (NSR), congestive heart failure patients (CHF) and myocardial infarction patients (MI). (a-f) energy content of the first six IMFs amplitude obtained by Hilbert-Huang transform.

Table -1: Significance for all empirical mode decomposition coefficients

Feature number	Classes			P-Value
	Normal Sinus Rhythm (NSR)	Congestive Heart Failure (CHF)	Myocardial Infarction (MI)	
	Mean $\pm$ S.D	**Mean $\pm$ S.D**	**Mean $\pm$ S.D**	
First	9.227 $\pm$ 7.093	14.7103 $\pm$ 11.42	23.6922 $\pm$ 17.826	4.0645e-010
Second	7.464 $\pm$ 6.199	8.0182 $\pm$ 5.239	8.4737 $\pm$ 6.333	0.5610 (ns)
Third	7.968 $\pm$ 5.634	13.6310 $\pm$ 9.616	12.7130 $\pm$ 10.492	5.3244e-004
Fourth	16.57 $\pm$ 12.21	7.9703 $\pm$ 5.800	25.9521 $\pm$ 20.044	7.5147e-010
Fifth	8.631 $\pm$ 5.479	9.4781 $\pm$ 7.061	10.0134 $\pm$ 7.798	0.4384 (ns)
Sixth	6.698 $\pm$ 5.256	17.3000 $\pm$ 12.55	27.2767 $\pm$ 22.087	2.1172e-013

6. CONCLUSION

This paper presents the application of the Hilbert-Huang transform to the HRV records. The basis functions of the Hilbert-Huang transform is the empirical mode decomposition method. This decomposition has the advantage of automatically identifying the intrinsic time scales of the data, including the longest scale (i.e the longer period oscillations) defined by the full length of the series,

without any presuppositions regarding the data's form. Hence, the components derived from the decomposition may carry actual physical significance.

Given the described nature of HRV series data, the Hilbert-Huang transform is a suitable and attractive method of analysis. it may overcome the current difficulty of achieving strictly stationary conditions, be appropriate to reflect the non-linear contents of the data, and may allow the study of the frequency information carried by the series as a function of time. Therefore, the HRV records were first analysed as a sequence of amplitudes describing the time dependent magnitude of the intrinsic mode functions (IMFs) such as energy content of the first six IMFs amplitude obtained by the Hilbert transform for each subject. Then, features were statistically analyzed by plotting the mean and standard error for each parameter in each cardiovascular disease. Results from ANOVA test show that this new technique is very encouraging and very promising. It helps in discriminating between normal subjects and patients with low heart rate.

In conclusion, the results of this paper suggest the use of the Hilbert-transform and the associated Hilbert spectral representation as powerful technique for HRV data time-frequency analysis, owing to the possibility of dealing with non-stationary and non-linear embedded phenomena, and perhaps owing to its suitability for a proper assessment of the dynamic and transient changes in amplitude and in frequency of the HRV components.

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