Analysis of Congestive Heart Failure ECG Signals Using Hilbert-Huang Transform

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Abstract

In this paper, the analysis of Congestive Heart Failure (CHF) electrocardiogram (ECG) signals has been performed using Hilbert-Huang Transform method for better diagnosis. ECG is a diagnostic tool that is routinely used to assess the cardiac abnormalities. CHF occurs when the normal pumping action is impaired, and the heart cannot pump enough blood to meet the body's needs. Signals of 10 CHF patients from Beth Israel Deaconess Medical Center (BIDMC) Congestive Heart Failure Database and signals of 10 healthy individuals from Fantasia Database from Physiobank were collected. Hilbert-Huang Transform (HHT) based analysis method is used in this study to examine the time-frequency-energy characteristics of Congestive Heart Failure ECG signals for efficient interpretation of various parameters of ECG signal. The ECG signal is decomposed to numerous intrinsic mode functions by empirical mode decomposition and the Hilbert energy spectra, instantaneous frequency, instantaneous amplitude are obtained using R environment. The statistical parameters like mean, standard deviation, energy of IMFs are calculated. The ratios of the energy for several IMFs of healthy and CHF ECG signals with respect to their corresponding total referred energy are compared and results are presented for better clinical diagnosis.

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1. Introduction

The heart works like a pump. It receives blood from the body and pumps it to the lungs, where it receives oxygen. This oxygen-rich blood is then pumped out to nourish the body. Heart failure is a common cardiovascular disease with high morbidity and mortality. Congestive heart failure occurs when this pumping action is impaired, and the heart cannot pump enough blood to meet the body's needs. When the heart cannot pump out the blood it receives, excess fluid may back up into the lungs and other body tissues. The decrease of nourishment to the body, and the overflow of fluid to the lungs, cause symptoms of congestive heart failure. It is a serious condition representing the end-

stage of a myriad of other cardiac diseases without a curative treatment. Once diagnosed, medication is required for the rest of the patient's life to improve their life quality and survival (Nasif et al., 2006). New York Heart Association Classifies CHF into four classes: Class I — No limitation during ordinary activity, Class II — Slight limitation by shortness of breath and/or fatigue during moderate exertion or stress, Class III — Symptoms with minimal exertion that interfere with normal daily activity and Class IV — Inability to carry out any physical activity without shortness of breath, which may be present even at rest. According to the American Heart Association updates in 2006, 5.3 million Americans have Congestive Heart Failure (CHF), 660,000 new cases are diagnosed yearly, with an incidence approaching 10 per 1000 population among persons older than 65 years of age. There are more than 20 million people affected worldwide and has a prevalence of 2% in developed countries (Nasif et al, 2006). The lifetime risk of developing CHF is one in five. The estimated yearly mortality related to heart failure is around 287 thousand people. Most of the CHF burden is borne by individuals aged ≥65 years, who account for more than 80% of the deaths and prevalent cases in the USA and Europe. In India, we do not have data regarding the exact prevalence and incidence of CHF. With higher propensity for cardiovascular diseases and ageing population, the burden of CHF is likely to be higher in comparison to the western population. Unlike western countries where CHF is predominantly a disease of elderly, in India it affects younger age group (Reddy et al, 2010). In India coronary artery disease, diabetes, hypertension, valvular heart diseases and primary muscle diseases are the leading causes for heart failure. The annual incidence of CHF for patients with Coronary Heart Disease (CHD) ranges from 0.4% to 2.3% per year, suggesting that 1,20,000 – 6,90,000 Indians could develop symptomatic CHF due to CHD every year. After 5 years, the total number of HF patients accrued could range from 6,00,000 to 3.5 million; with an estimated 50% mortality at 5 years. Nevertheless, as the prevalence of patients with CHD rises, so too will the prevalence of patients with CHF. The prevalence of other risk factors of HF is also rising in India. CHF in India has reached epidemic proportions (Huffman et al., 2010). Despite many recent advances in medication, the rate of people with chronic congestive heart failure is rising. Incorporating effective, comprehensive prevention of CHF provides the best opportunity to curb the projected rise of CHF in India. Early identification of the risk factors and initiation of appropriate therapy at early stages prevents development of heart failure. Clinical diagnosis and diagnostic imaging identifies patients with heart failure but it seems to be a challenging problem.

The electrocardiogram (ECG) has many established applications useful for the diagnosis, management, and follow-up of patients with congestive heart failure (CHF). Since CHF can be the

outcome of many pathophysiological derangements, the ECG of such patients may show a large range of abnormalities. Occasionally patients with CHF may have a normal ECG, or merely show sinus tachycardia without any other abnormalities. More commonly however, the ECG of patients with CHF may reveal left ventricular hypertrophy (LVH), all types of atrial and ventricular arrhythmias, atrio-ventricular and intra-ventricular conduction blocks, evidence of myocardial ischemia and/or myocardial infarction, right ventricular hypertrophy, and left and right atrial abnormalities. For patients with CHF with peripheral edema in heart found to have attenuation in ECG waveform of CHF patients, that is, lower amplitudes of QRS complexes and P waves, shortening of QRS duration. Thus detailed analysis of ECG for patients with other cardiac abnormalities helps in early detection prediction of risk of CHF in patient and hence improve the diagnostic accuracy of clinicians (Madias et al, 2009).

The traditional spectrum estimation based on Fast Fourier Transform (FFT) which is best suited for stationary signal analysis loses its robustness when applied for physiological signal analysis with non-stationary characteristics. An efficient diagnosis using the latest signal processing approaches is need of the hour and hence analysis by Hilbert-Huang transform (HHT) have been applied in this work for better and reliable clinical analysis. HHT is one of the promising methods of time-frequency analysis, and it is suitable for the analysis of non-stationary signals. It is an empirically based data analysis method. Its basis of expansion is adaptive, so that it can produce physically meaningful representations of data from non-linear and non-stationary processes.

HHT is a robust method for the analysis ECG signal using empirical mode decomposition (EMD). This method has numerous clinical applications, specifically in feature extraction and instantaneous frequency. In all the cases studied, HHT gave results much sharper than those from any of the traditional analysis methods in time-frequency-energy representations (Yacin et al., 2013; Yacin and Vennila, 2015). The aim of EMD is to decompose the signal into intrinsic mode functions (IMFs). An IMF represents the oscillatory mode embedded in the data. The reason behind using the EMD lies in the fact that lower order IMFs capture fast oscillation by higher IMFs typically represents slow oscillation modes. The lower order IMFs of ECG can be used to distinguish the QRS complex in the ECG signal whereas a high P or T waves can be obtained from the higher order IMFs. In contrast with other techniques, the time-frequency representation of data in HHT does not involve spurious harmonics and hence can present more natural and quantitative results. The rational for this statement can be justified by its ability to enable and implementation of a novel concept: using instantaneous frequency (IF) to describe the spectral data.

In Section 2, data collection and mathematical implementation of the HHT are reviewed. In Section 3 deals with the results of the proposed method, the discussion of which is also reported. A conclusion about the approach, together with some remarks on the future work, has been noted in Section 4.

2. Materials and Methods

2.1. Hilbert-Huang Transform

The HHT is a new mathematical tool for time-frequency analysis, developed by Huang et al, 1998. It comprises of empirical mode decomposition and Hilbert spectral analysis (Huang et al., 1996, 1998, and 1999). In this section, we will introduce briefly both components of HHT and present some properties of HHT. It will be shown that the Hilbert transform (HT) can lead to an apparent time-frequency-energy description of a time series; however, this description may not be consistent with physically meaningful definitions of instantaneous frequency and instantaneous amplitude. The EMD can generate components of the time series whose Hilbert transform can lead to physically meaningful definitions of these two instantaneous quantities, and hence the combination of HT and EMD provides a more physically meaningful time frequency-energy description of a time series.

Empirical Mode Decomposition Method: In the EMD technique the signal is first decomposed into a set of simple functions called Intrinsic Mode Function (IMF). Definition and further details about IMF properties and extraction can be found in the literature (Huang et al., 1996, 1998, and 1999). A systematic way for extracting IMF from a complicated data set is known as sifting. The EMD method, first proposed in 1998 by Huang et al, decomposes any given time series data into a set of simple oscillatory functions that are defined as intrinsic mode function (IMFs), $h_m(t)$, i=1,2,…….n, and the residual $r(t)$, in the following way,

$$\mathbf{x(t)} = \sum_{\mathbf{n=1}}^{\mathbf{N}} \mathbf{h_n(t)} + \mathbf{r(t)} \qquad (1)$$

The IMF's are a set of well-behaved intrinsic modes, which can be applied by the Hilbert Transform (HT). The idea behind this approach is that every IMF has a very narrow frequency band all time, which allows us to produce a time-frequency spectrum called Hilbert-Huang (HH) spectrum by using the Hilbert transform. The decomposition process can be called as sifting process. The goal of sifting is to subtract the large-scale features of signal repeatedly until only the fine-scale features remain. The sifting process ends when the residue r(t) satisfies a predefined stopping criterion which is given by,

$$SD_k = \frac{\sum_{t=0}^{T}|m_{1k}(t)|^2}{\sum_{t=0}^{T}|h_{1k}(t)|^2} \quad (2)$$

Convergence criteria typically consist of testing if the residual is either smaller than a predetermined value or a monotonic function, $h_n(t)$, for n= 0, 1, 2, ..., n are being sorted in descending orders of frequency. Finally, the original $x(t)$ can be reconstructed by a linear superposition shown in equation (1).

Each IMF should have the two properties. First, along the signal, the number of extrema and the number of zero crossings must either be equal or differ at most by one. Second, at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. Once the highest frequency is removed from a signal, the same procedure is applied on the residue signal to identify next highest frequency. The residue is considered a new signal to decompose. Figure 2 shows the IMF's for normal sinus rhythm (NSR) and Figure 3 shows the IMF's for CHF ECG using EMD technique.

Hilbert Spectral Analysis: As emphasized in the previous section, the purpose of the development of HHT is to provide an alternative view of the time frequency-energy paradigm of data. In this approach, the nonlinearity and non-stationarity can be dealt with better than by using the traditional paradigm of constant frequency and amplitude. One way to express the non-stationarity is to find instantaneous frequency and instantaneous amplitude. This was the reason why Hilbert spectrum analysis was included as a part of HHT. For any function x(t) of L^p class, its Hilbert transform y(t) is,

$$\boldsymbol{y(t)} = \frac{\mathbf{1}}{\pi}\, \boldsymbol{P} \int_{-\infty}^{\infty} \boldsymbol{x}\left(\frac{\tau}{t-\tau}\right) \boldsymbol{d\tau} \quad (3)$$

where P is the Cauchy's principal value of the singular integral. With the Hilbert transform y(t) of the function x(t), we obtain the analytic function,

$$z(t) = x(t) + i\, y(t) = a(t)\, e^{i\theta(t)} \quad (4)$$

where $i = \sqrt{-1}$,

$$a(t) = (x^2 + y^2)^{1/2}\ ,\ \theta(t) = \tan^{-1}\frac{y}{x} \quad (5)$$

Here, a as the instantaneous amplitude, and q as the instantaneous phase function. The instantaneous frequency is expressed as,

$$\omega = \frac{d\theta}{dt} \quad (6)$$

With both amplitude and frequency being a function of time, we can express the amplitude (or energy, the square of amplitude) in terms of a function of time and frequency, *H (w, t).*

2.2 Methodology

Data Collection: Physiobank is a large and growing archive of well-characterized digital recordings of physiological signals and related data for use by the biomedical research community. The data used in this study is from BIDMC Congestive Heart Failure database. Beth Israel Deaconess Medical Center (BIDMC) in Boston, Massachusetts is a teaching hospital of Harvard Medical School. This database includes long-term ECG recordings from 10 subjects (7 men, aged 22 to 71, and 3 women, aged 54 to 63) with severe congestive heart failure (NYHA class 3-4). This group of subjects was part of a larger study group receiving conventional medical therapy prior to receiving the oral inotropic agent, milrinon. The individual recordings are each about 20 hours in duration, and contain two ECG sampled at 250 samples per second with 12-bit resolution over a range of ±10 millivolts. The original analog recordings were made at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center) using ambulatory ECG recorders with a typical recording bandwidth of approximately 0.1 Hz to 40 Hz.

Electrocardiographic signals of 10 rigorously-screened healthy elderly (68 - 85 years old) subjects were collected from FANTASIA database in Physiobank. All subjects remained in a resting state in sinus rhythm while watching the movie Fantasia to help maintain wakefulness. The continuous ECG signals were digitized at 250 Hz. This reliable database was taken for the analysis of cardiac abnormalities by Hilbert-Huang transform.

Data Assessment: For Hilbert spectral analysis, The R package EMD (Kim and Oh, 2008) that performs one and two- dimensional EMD and HS was used. The above-mentioned decomposition process is implemented by the function *emd()* that utilizes the functions *extractimf()* and *extrema()*.

```
> ### Empirical Mode Decomposition
> par(mfrow=c(3,1), mar=c(2,1,2,1))
> try <- emd(xt2, tt2, boundary="wave")
```

The local information can be described by the Hilbert spectrum which is amplitude and instantaneous frequency representation with respect to time. The X-Y axis represents time and instantaneous frequency, and the color intensity of the image depicts instantaneous amplitude.

```
> ### Spectrogram : X - Time, Y - frequency,
> ### Z (Image) - Amplitude
> test1 <- hilbertspec(interm1$imf)
> spectrogram(test1$amplitude[,1],
+ test1$instantfreq[,1])
> test2 <- hilbertspec(interm2$imf, tt=tt)
> spectrogram(test2$amplitude[,1],
+ test2$instantfreq[,1])
```

For multiple signals, the function hilbertspec() calculates the amplitudes and instantaneous frequency using Hilbert transform. The function has the following arguments,

- xt : matrix of multiple signals. Each column represents a signal.
- tt : observation index or time index.

The function hilbertspec() returns a matrix of amplitudes and instantaneous frequencies for multiple signals. The function spectrogram() produces an image of amplitude by time index and instantaneous frequency. The horizontal axis represents time, the vertical axis is instantaneous frequency, and the color of each point in the image represents amplitude of a particular frequency at a particular time. It has arguments as,

- amplitude: vector or matrix of amplitudes for multiple signals.
- freq: vector or matrix of instantaneous frequencies for multiple signals.
- tt: observation index or time index.
- multi: specifies whether spectrograms of multiple signals are separated or not.
- nlevel: the number of color levels used in legend strip
- size: vector of image size.

Flow diagram of the above complete signal processing stages in estimating HHT Spectrum are pictorially represented in Figure 1.

Energy and Energy ratio: The statistical parameters such as minimum amplitude, maximum amplitude, mean, and standard deviation, energy and energy ratio were calculated. The energy and energy ratio gives the strength of the signal. The referred total energy of HHT-based signal is defined as follows:

$$E_r(t) = \sum_{i=1}^{L} IMF_i^2(t) + RF^2(t) \quad (7)$$

Where, $IMF_i(t)$ is the ith IMF and RF(t) is the residual function. The ratio of the energy of a wave to its referred total energy for the ith IMF is expressed as follows [Zhu et al, 2015]:

$$ER_{imf} = \frac{IMF_i^2(t)}{E_r(t)} \times 100\% \quad (8)$$

3. Results and Discussion

The Empirical mode decomposition applied on a subject results in nine intrinsic mode functions and a residual function. Figure 2 illustrates the result of decomposition performed by EMD of a NSR. Figure 3 shows that the first mode has a higher frequency than the second mode where modes are ordered from the highest frequency to the lowest. The main components of the ECG signal are located in the first four modes and the lower modes indicate artifact, trend and low-frequency ECG. In contrast, Figure 3 shows the result of the decomposition applied to a CHF ECG signal with the main components of ECG signal located in the first four modes. A visual comparison between Figure 2 and Figure 3 may lead to a qualitative discrimination. As mentioned previously, a quantitative discrimination can be applied by means of Hilbert-Huang spectrum based on local frequency/amplitude information. The intrinsic mode function decomposed from the NSR and CHF ECG signals can be processed via the Hilbert transform in which the size of the amplitude is marked with different colors; so, color variation reveals ECG signal energy distribution in the time domain and frequency domain. Figure 2 indicates the Hilbert spectrum for NSR - Energy concentrated in lower frequency that ranges up to 30 Hz. Figure 3 indicates the Hilbert spectrum of CHF ECG signal in which energy concentrated in frequencies that ranges up to 120 Hz. The statistical parameters such as minimum amplitude, maximum amplitude, mean, and standard deviation, energy and energy ratio were calculated.

The data analysis results showed that the Hilbert spectrogram of CHF ECG signal has the amplitude (energy) distribution concentrated in both, lower and higher frequency range, which ranges till 120 Hz whereas the Hilbert spectrogram of NSR has the amplitude (energy) distribution concentrated in lower frequency range, which ranges till 60 Hz. It is due to the reason that the ECG signal of CHF patients found to have shortening of QRS complexes and hence increase in amplitude distribution over a large frequency range. Energy Ratio (ER) is considered as main feature in which discrimination between NSR and CHF ECG signal is based upon. The Energy Ratio (ER)

comparison (Table I) showed that the ratios of energy of IMF1, IMF2, IMF3, and IMF4 of the CHF ECG signal to their total refereed energy were found to be less when compared to normal sinus rhythm. It has been found that this energy ratio of IMF1 of CHF ECG signal lies below 5% whereas the energy ratio of NSR were greater than 10% in most of the cases. This is because of the reason that the CHF ECG signal have attenuations in QRS complexes, that is, reduction in the strength of the signal and hence the reduction in the energy and energy ratio of IMFs of CHF ECG signal when compared to the IMFs of NSR. The statistical parameters such as maximum amplitude, minimum amplitude, mean, standard deviation that were calculated from the IMFs of ECG signals was useful to find out the highest and lowest amplitudes and their mean and standard deviation at various stages of intrinsic modes of the CHF ECG for better interpretation and comparison of the ECG signals.

5. Conclusion

The Congestive Heart failure disorder is greatly harmful to life and is mostly prevalent among aging populations. The ECG signal of CHF patients were found to be abnormal with attenuated QRS complexes and P-waves and shortening of QRS duration and QT intervals. In the paper, we analyzed the Time-Frequency-Energy distributions of the intrinsic mode functions (IMFs) for the NSR and the ECG signals recorded from congestive heart failure subjects. The results show that the proposed time-frequency-energy distribution technique and comparison based on energy ratio is useful for the classification of CHF ECG, with reasonably high accuracies has been proven to be promising tool for ECG signal analysis. Our future works are devoted to examine more characteristic parameters from IF, IA and IMF signals of CHF ECG signals of all leads to enhance the diagnosis to a greater extent. Furthermore, the study can be extended to for analysis of other physiological signal for improved diagnosis of diseases by clinicians.

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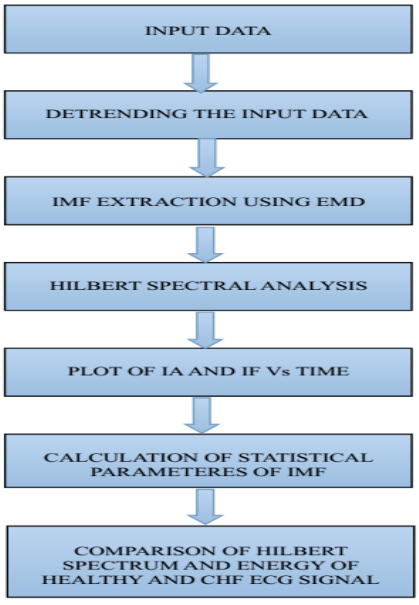

Figure 1. Flow diagram of the complete signal processing stages in estimating HHT Spectrum

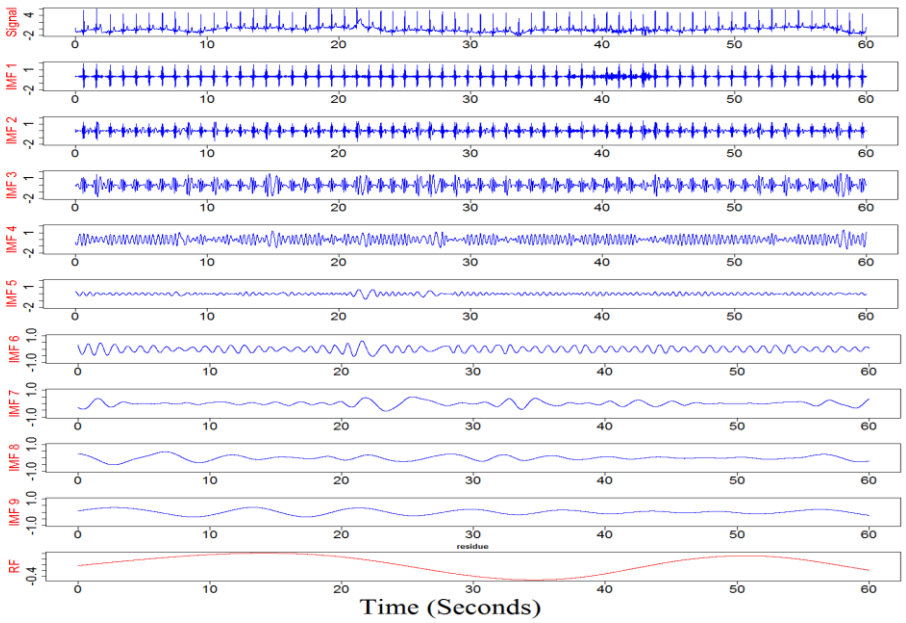

Figure 2. NSR - Original signal, IMF 1 - IMF 9 and RF

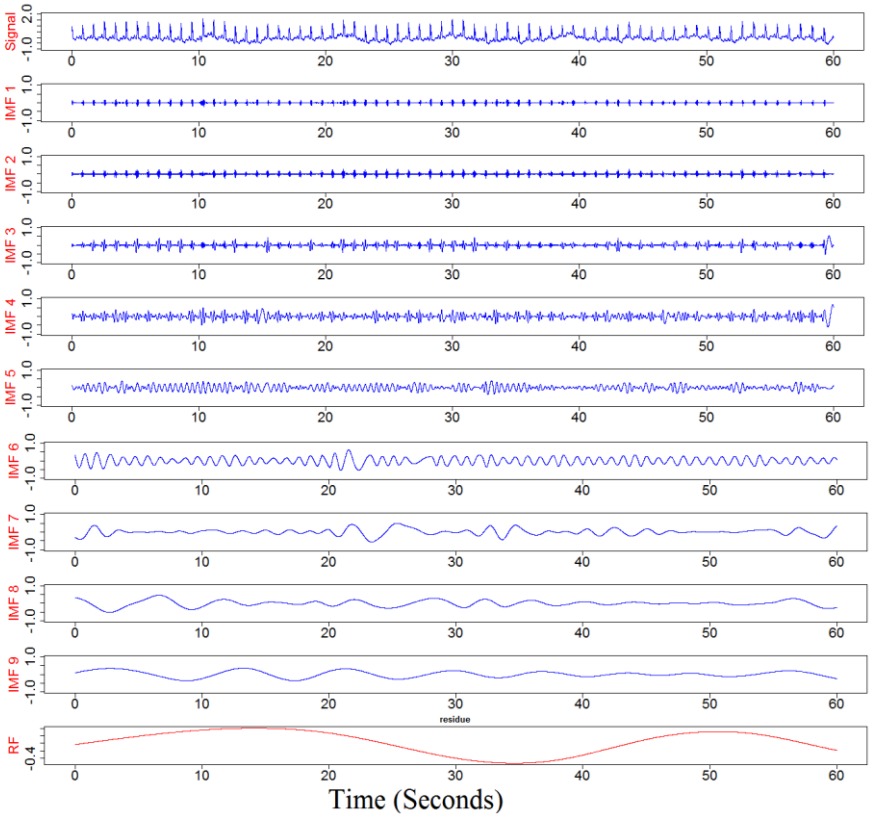

Figure 3. NSR - Original signal, IMF 1 - IMF 9 and RF

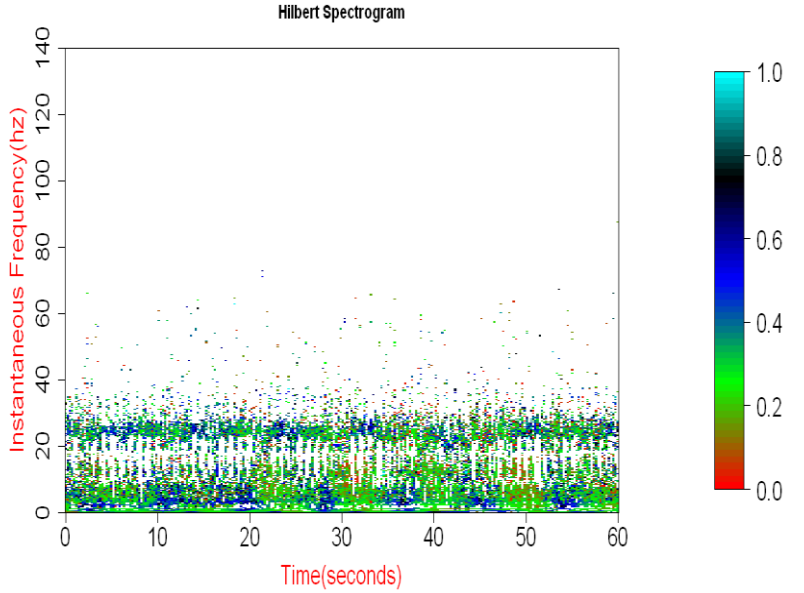

Figure 4 Hilbert Spectrum of a NSR

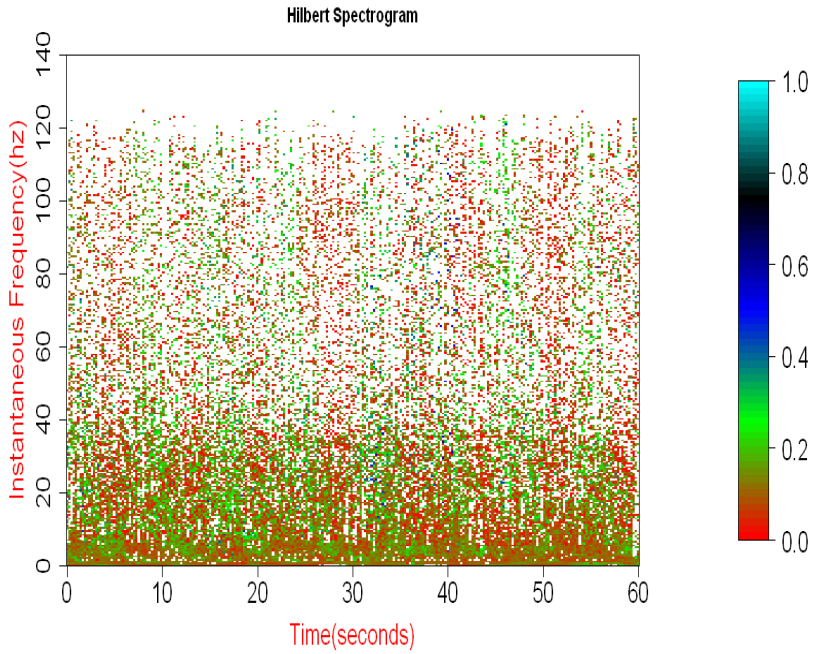

Figure 5. Hilbert Spectrum of a CHF ECG signal

Table I Comparison of the Energy ratios of NSR and CHF subjects

	NSR 1	**NSR 2**	**NSR 3**	**NSR 4**	**NSR 5**	**NSR 6**	**NSR 7**	**NSR 8**	**NSR 9**	**NSR 10**
ER-IMF1	13.72	13.38	0.32	10.81	8.9	4.44	4.19	20.76	6.62	15.14
ER-IMF2	10.8	11.53	2.11	23.12	17.75	8.23	10.3	22.4	8.49	18.91

ER-IMF3	21.21	17.68	2.1	23.96	31.46	23.86	31	20.43	26.74	25.04
ER-IMF4	27.07	20.86	1.44	25.59	28.85	35.61	34.72	15.38	26.09	17.6
ER-IMF5	8.7	17.88	1.53	6.99	7.87	9.87	11.55	7.03	14.02	9.86
ER-IMF6	1.97	4.9	1.19	1.4	1.23	4.68	3	4.82	5.01	4.5
ER-IMF7	2.26	4.55	0.54	5.41	1.72	6.54	3.57	5.22	2.32	5.11
ER-IMF8	2	2.1	5.49	0.59	0.83	2.25	0.72	0.58	1.69	1.15
ER-IMF9	2.6	1.83	35.38	0.84	0.83	2.25	0.67	1.35	0.64	0.68
ER-RF	9.66	5.3	49.89	1.29	0.58	2.27	0.28	2.03	8.38	2.02
	CHF 1	**CHF 2**	**CHF 3**	**CHF 4**	**CHF 5**	**CHF 6**	**CHF 7**	**CHF 8**	**CHF 9**	**CHF 10**
ER-IMF 1	1.4	0.22	2.14	0.95	3.74	0.79	0.93	4.38	0.29	1.98
ER-IMF 2	2.86	0.93	9.41	2.99	4.77	16.24	1.01	7.61	3.64	25.34
ER-IMF 3	10.05	6.77	14.76	16.12	13.33	20.72	1.88	12.72	11.47	15.82
ER-IMF 4	20.32	12.73	15.65	13.09	14.86	20.03	1.81	20.54	21.6	23.03
ER-IMF 5	19.48	23.91	7.82	19.69	13.56	12.28	2.41	21.04	28.11	17.69
ER-IMF 6	23.92	32.08	15.1	32.65	30.43	9.03	2.92	20.7	21.37	7.51
ER-IMF 7	10.34	14.65	7.88	4.22	9.34	1.75	11.1	2.82	2.6	3.38
ER-IMF 8	3.32	2.47	8.87	1.22	4.1	2.60	31.44	3.35	0.59	1.94
ER-IMF 9	4.99	1.99	5.67	5.4	0.61	14.87	41.21	3.58	2.37	2.69
ER-RF	3.32	4.26	12.69	3.66	5.27	1.70	5.3	3.26	7.95	0.63