WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

HRV ANALYSI USING DICRETE WAVLATE TRANSFORM

[a*]Chetan Choudhary , [b]Anupam Kumar Gautam

[a]Maharishi University of Information Technology, Lucknow,226013
[b]Maharishi University of Information Technology, Lucknow,226013

A B S T R A C T

ECG is a method for measuring the rate and regularity of heartbeats in order to detect any irregularities in the heart. An ECG converts the electrical activity of the heart into a wave-line on paper or a screen. In order to perform the classification task, the Discrete Wavelet Transform (DWT) will be used to extract relevant information from the ECG input data. It is presented a method for analysing Heart Rate Variability (HRV) signals using the Wavelet transform. Wavelet transform analysis is an alternative tool for analysing nonstationary signals with changing spectral characteristics over time. The Wavelet transform is a timescale processing method in two dimensions. Because of its adequate scale values and time shifting, DWT is appropriate for nonstationary ECG signals. . The data will be analysed and classified using BIOPACK in this case. MATLAB software is used to validate the proposed method using various ECG signals. A specially adapted decomposition-reconstruction filter bank for the frequency bands of interest is included in the design and implementation. For the very low frequency (VLF), low frequency (LF), medium frequency (MF), and high frequency (HF) bands, a time-scale representation is obtained. Our findings suggest that wavelet analysis could be a useful tool for evaluating the time frequency oscillatory components of biological signals.

1. INTRODUCTION

Wavelet analysis is useful for problems in which signals have distinct morphology, with different spectral signatures assigned to different parts of the waveform, and the events of diagnostic interest are well localized in time and scale. The wavelet transform works on the principle of hierarchically decomposing an input signal into a series of successively lower resolution reference signals and their associated detail signals.

HRV (heart rate variability) is a well-known tool for estimating cardiac autonomic modulations. HRV physiology has recently advanced significantly, and studies of HRV now allow for detailed assessment of cardiac autonomic status under complex conditions. HRV's established clinical applications are currently limited to risk assessment after myocardial infarction and early diagnosis of diabetic neuropathy [1].

HRV signals have been analyzed using a variety of techniques. The discrete Fourier transform is the most widely used technique in the frequency domain. It is simple and fast, but due to its lack of time resolution, it is only suitable for stationary signals. New techniques with superior time-frequency resolution are required for non-stationary signals such as HRV. Furthermore, HRV analysis must be performed during times when the cardiovascular system maintains its characteristics over time in order to obtain accurate estimates and correctly interpret the overall experimental results. For all of these reasons, one technique that has both satisfactory time and frequency (scale) resolution could be the wavelet transform. [14]Wavelet transform has recently been used for time-frequency domain analysis. This transform acts as a filter, extracting time-dependent signals from the original signal in a specific frequency band. Thus, wavelet transform can decipher temporal and localised changes in physiological signals, as well as effectively quantify time-varying changes in HRV. A study of ECG records was conducted in this work to evaluate the possibility of analysing heart rate variability with the wavelet transform, with an emphasis on the time evolution of the different frequency components of the HRV signal. This thesis discusses important wavelet transform features in HRV power spectrum estimation and its extension to sympathovagal balance estimation[2].

The ability of this technique to track the time evolution of the various frequency components separately. Figure (1)

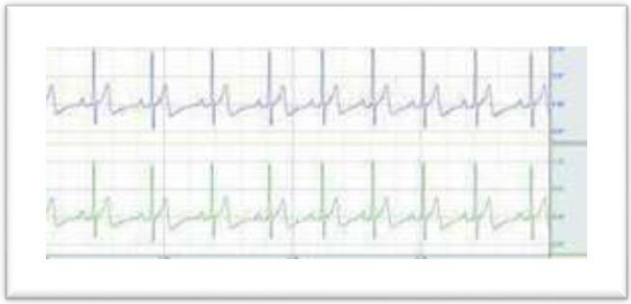


Figure 1 (ECG) Electrocardiogram Signal

2. PHYSIOLOGICAL VARIABLES MEASUREMENT

ECG; physiological variables EEG pulse rate The MP100 system is used to measure blood pressure, respiration rate, and other parameters. In my dissertation, ECG is measured using the MP100 system for HRV analysis. These variables are recorded for various subjects as well as for the same subject under various conditions.

The MP100 system is a computer-based data acquisition system that performs many of the same functions as a chart recorder or other data viewing device, but is superior in that it exceeds the physical limits commonly encountered with such devices (such as paper width or speed). The MP data acquisition unit (MP100) is the MP system's heart. The MP unit converts incoming signals into digital signals that can be processed by your computer.

ECG, EEG, EMG, EOG, Evoked response, Plethsmography, Pulmonary Function, and other applications are possible with the MP system.

In general, data collection entails receiving an incoming signal (usually analogue) and sending it to a computer, where it is (a) displayed on the screen and (b) stored in the computer memory (or on the disc). Figure 2 and figure 3 show bio pack system[3]

The system is designed to satisfy the following Medical Safety Test Standards affiliated with IEC601-1:

1. Cree page and Air Clearance
2. Dielectric Strength
3. Patient Leakage Current

2.1 MP100 Block Diagram

MP100 system includes:

1. Data acquisition unit:MP100C
2. Universal interface module:UIM100C
3. USB adapter:USB1W(PC) or USB1M(Macintosh)
4. Transformer:AC100A Cables:CBLSERA cable, CBLS100 cable set

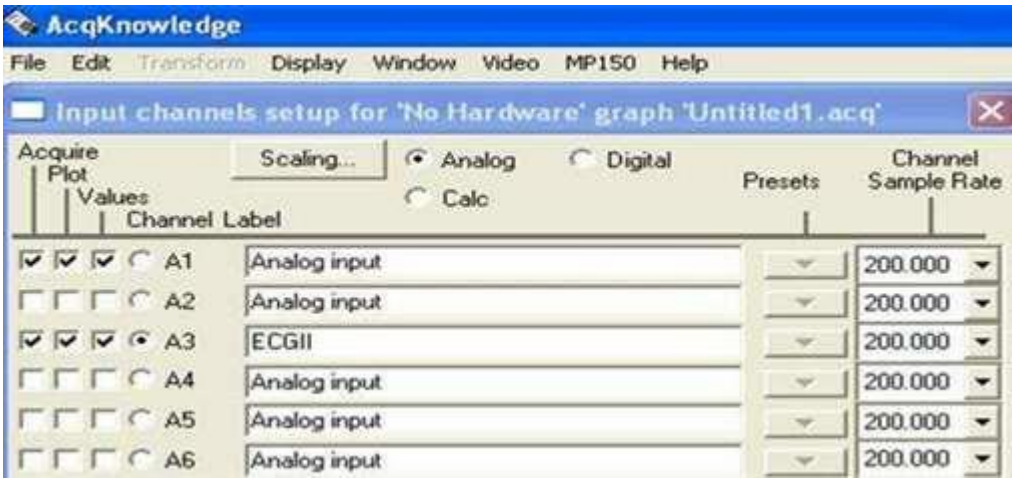


Fig 2.1 Input channels setup for MP100

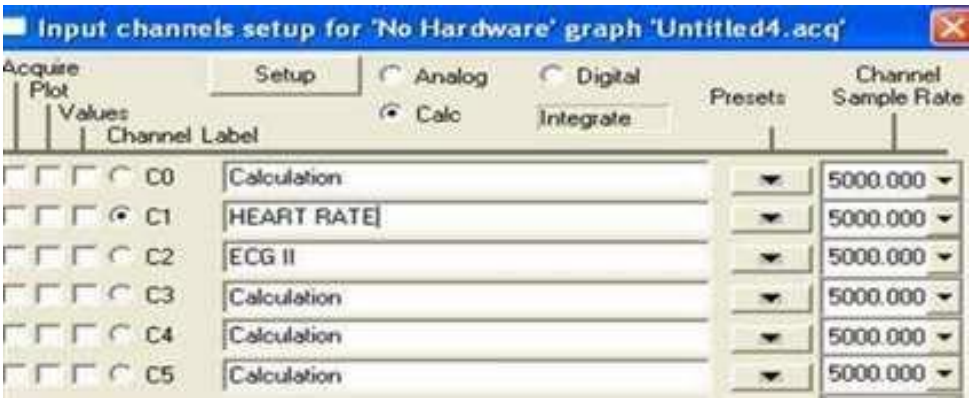


Fig 2.2 Input channels setup

Calculation Presets are the like templates for calculation channels. Each preset stores:

1. Calculation channel type
2. Parameters for that calculation
3. Channel specific scaling
4. Channel specific sampling rate
5. Channel name

The variable sampling rate feature allows different data channels to be down sampled from the acquisition sampling rate; the calculation channel must use a sampling rate that is less than or equal to the source channel. Choosing a lower sampling rate for signals where meaningful data falls below the acquisition sampling rate's Nequist frequency allows for more data to be stored in memory or on disc.[4]

Figure 2.3 Photograph of complete Experimental Setup

3. ECG MEASURMENT

The ECG records the electrical activity of the heart, with each heartbeat displayed as a series of electrical waves with peaks. Any ECG provides two types of data. The duration of the electrical wave crossing the heart determines whether the electrical activity is normal, slow, or irregular, and the amount of electrical activity passing through the heart muscle determines whether the parts of the heart are too large or overworked. ECG signals have a frequency range of 0.05-100 Hz and a dynamic range of 1-10 mV. The ECG signal is defined by five peaks and valleys denoted by the letters P, Q, R, S, and T. In some cases, we also employ another peak known as U. The accuracy and reliability of the QRS complex, as well as T- and P waves, are critical to the performance of an ECG analysing system. The P-wave represents the activation of the heart's upper chambers, the atria, whereas the QRS complex and T-wave represent the activation of the heart's lower chambers, the ventricles. The most important task in automatic ECG signal analysis is detecting the QRS complex. Once the QRS complex has been identified, the ECG signal can be examined in greater detail, including the heart rate, the ST segment, and so on. ECG is showed in figure 3.1

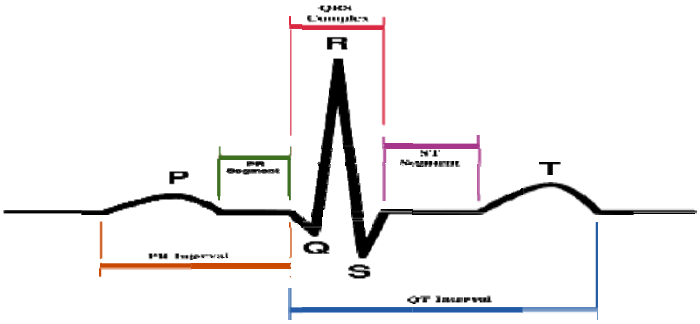


Fig 3.1 Schematic representation of normal ECG

Heart Rate Variability

Heart rate variability (HRV) is a measurement of heart rate variations from beat to beat. It is typically calculated by analyzing a time series of beat-to-beat intervals from an ECG, beat-to-beat intervals from an arterial pressure trace, or beat-to-beat intervals from a pulse wave signal measured with a Photoplethysmograph (PPG).

There have been several proposed measures of heart rate variability, which can be roughly divided into time domain, frequency domain, and geometric measures. Although HRV is regarded as an indicator of the activity of autonomic regulation of circulatory function, there is debate as to whether this is an accurate metric for analyzing cardiovascular autonomic control. HRV changes (mostly decreases) have been linked to a variety of pathologic conditions, including hypertension, Septic shock and hemorrhagic shock It is also useful as a modest predictor of mortality following an acute myocardial infarction. [22][23]

4. WAVELET TRANSFORM INTRODUCTION

Though some of the ideas behind the wavelet transform have been around since the early part of the 20th century, the formalization of wavelet theory was only recently initiated by geophysicists involved in seismic signal analysis (Goupillaud, et al., 1984; Gross-mann and Morlet, 1984, Morlet, et al., 1982). The theory was refined by researchers in the mathematical community (Daubechies, 1992) and in the signal processing community (Mallat, 1989; Vetterli and Herley, 1992; Vetterli and Kovacevic, 1995). In this and proceeding section the wavelet transform is defined(both continuous time and discrete-time)and the advantages of this type of transform are highlighted.[6][7]

Fourier's transformation statistically represents the Fourier analysis process:

$$F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-j\omega t} dt$$

Which is the sum of the signal f(t) over all time multiplied by a complex exponential (Recall that a complex exponential has real and imaginary sinusoidal components).[5]

Figure 4.1 Fourier transform of the signal

The Fourier coefficients are the transform's output, which when multiplied by a sinusoid of frequency yield the original signals

Similarly, the continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function:

$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)dt$$

The CWT produces a large number of wavelet coefficients C that vary with scale and position. The constituent wavelets of the original signal are obtained by multiplying each coefficient by the appropriately scaled and shifted wavelet:[8][9]

(a)

(b)

Figure 4.2 (a) Wavelet transform of the signal (b) Graphical Wavelet transform

Discrete-Time Wavelet Transform(DTWT) and Perfect Reconstruction Filter Banks(PRFB)

Though the CWT is useful for mathematical derivation of Wavelet transform thermos and properties, in computational application(where signal and filter are discrete),it is the DTWT that is used. The DTWT is generally implemented using filter bank. Figure 4.3 [11][12]

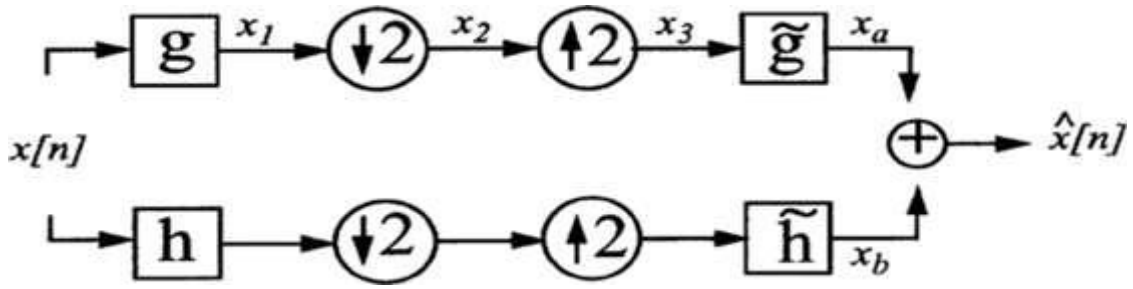


Figure 4.3 -Two Band filter bank

5. HRV ANLYSIS USING DISCRETE WAVELET

In this work, a study of ECG records to evaluate the possibility of analysis of heart rate variability with the discrete wavelet transform with emphasis on the time evolution of the different frequency components of HRV signal. The ability of this technique to track separately the time evolution of the different frequency components and more effective quantification of time varying changes of HRV signals have been demonstrated. Therefore our aims were find in three part(a) the analysis of ECG signal in different position (b) to find the R-R interval techogram (c) decomposition of R-R techogram interval to find the LF ,HF ,VLF .[7]

The analysis Lead II ECG is recorded by using electrocardiogram amplifier module(ECG 100C) in BIOPACK. ECG100 is a single channel ,high gain, differential input ,biopotential amplifier designed specifically for monitoring the hearts activity .It has built in derive capability for use with shielded electrode leads .It is designed to pass the ECG signal (P,Q,R,S,T) with minimal distortion.

The best choice of electrode depends on the application but typically the EL500 series of disposable snap electrode are used in conjunction with LEAD 110S pinch lead .In our system Ag-AgCl disposable lead electrodes are used.[18]

Three electrodes are used to record Lead II ECG signal . Two active electrode are affixed on right arm(RA) and left leg(LL) .Reference electrode is applied on right leg(RL) of the subject. The electrodes are connected to the ECG amplifier (ECG 100C) using three leads.

The ECG 100C include a high pass filter that is used to stabilize the ECG bas line. When the switch is set to 1.0 HZ, P and T wave amplifier will be reduced somewhat, but the QRS wave will be virtually unchanged. The HP switch is usually ON when using the ECG 100C for rate measurement only or when monitoring the ECG of an active subject .[8]

In this we analyze the more then one subject ECG signal to find out the R-R interval techogram for HRV .figure 5.1

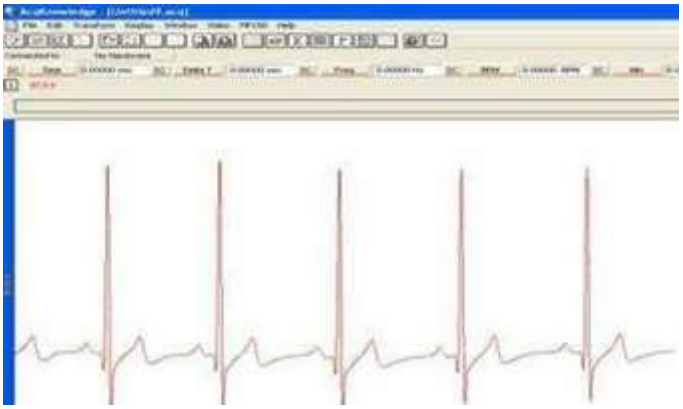


Figure 5.1 Lead II ECG recorded using ECG amplifier

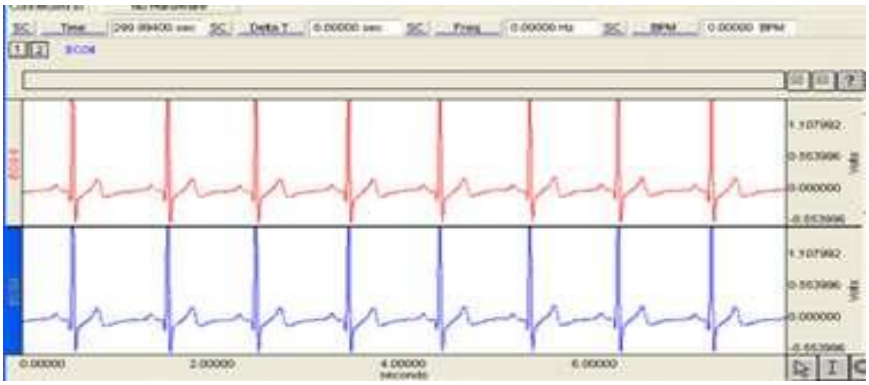


Figure 5.2 Lead II ECG recorded using BIOPACK

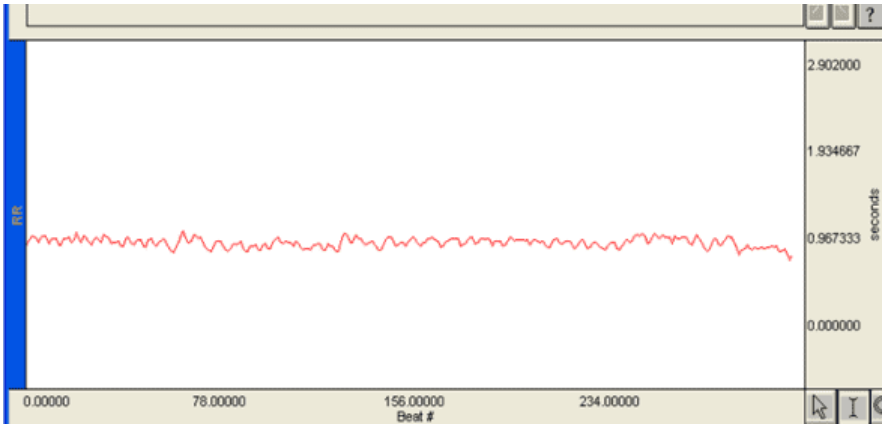


Figure 5.3 –R-R Interval Techogram

DWT in HRV Analysis

For discrete-time signals, the dyadic discrete wavelet transform (DWT) can be implemented as a cascade of low-pass and high-pass finite impulse response filters as illustrated in Figure 5.7 [14][15]. The signal is decomposed at each scale into its detail (high-pass) and approximation (lowpass) signals and down-sampled. The detail signal is then stored and the decomposition continues by filtering the approximate signal as the input signal for the next scale. At each scale j , the frequency axis is recursively divided into halves at the ideal cut-off frequencies. For the purpose of wavelet analysis, the dyadic decomposition has forced to choose a sampling frequency of 4.8 Hz and to take decomposition level, J = 8 in order to have the best possible correspondence between physiological subbands and resulting dyadic frequency bands .The resulting bands are VLF = 0.01875 - 0.0600 Hz, LF = 0.0375 - 0.15 Hz, and HF = 0.015 - 0.60 Hz. The discrete wavelet transform algorithm is implemented using the Daubechies wavelet (DW) as shown in Fig 4.8[19]

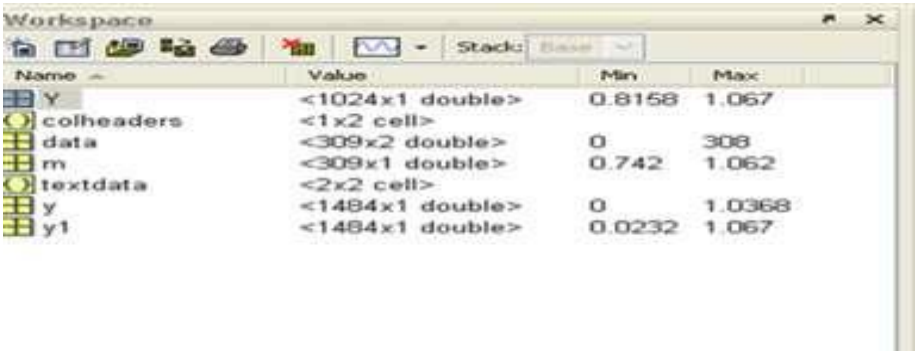


Figure 4.8 R-R Interval Resampling at Rate 4.8 Hz

Figure 4.9 Decomposition of R-R Interval At 8 Level Using db4

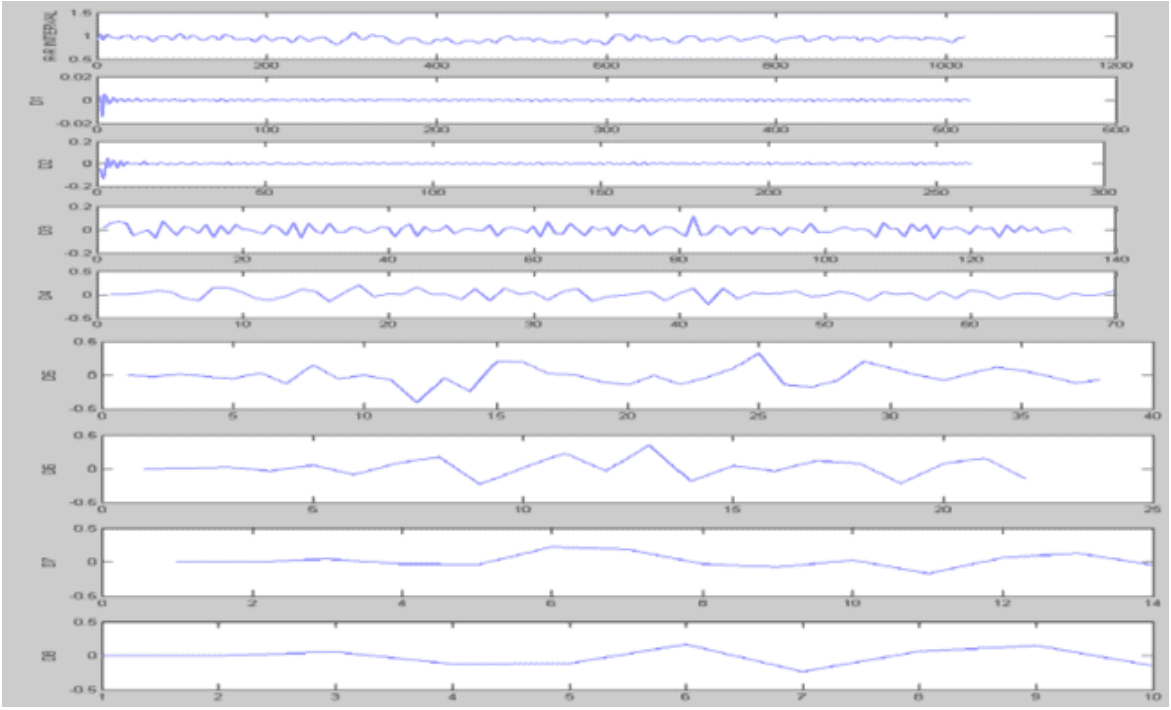
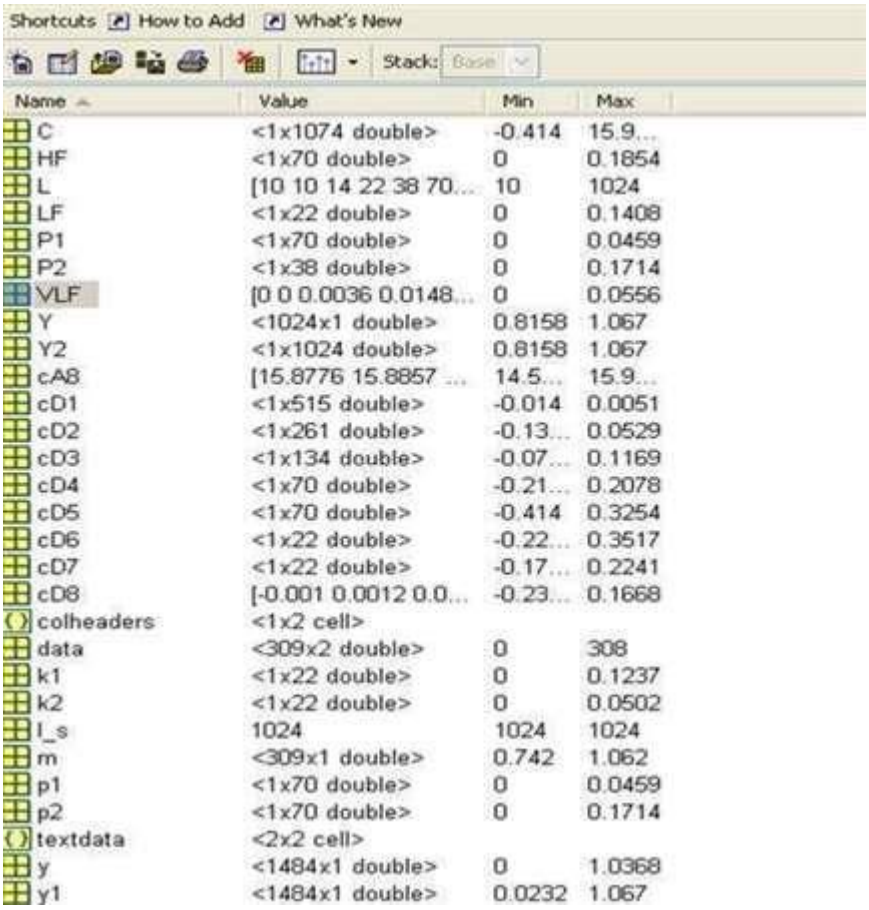


Figure 4.10 –R-R Interval Decomposition Signal At 8 Level by db4



(a)

Figure 4.13-Finding HRV Component HF , LF, VLF

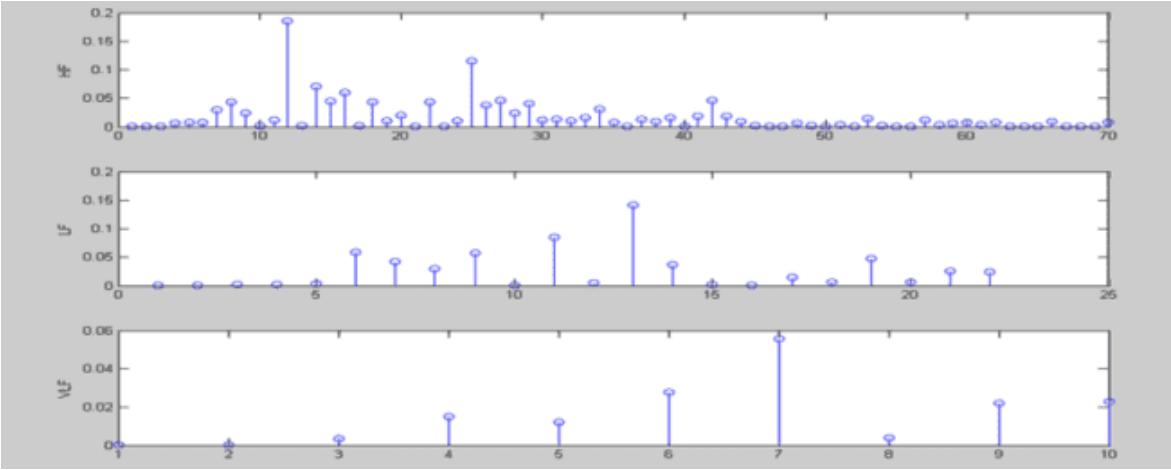


Figure 4.14–HRV Component Signal HF,LF and VLF

In the figure show that the first we decomposed the R-R interval techogram at eight level at 4.8 sampling rate by using Daubechies wavelet (db4) .After decomposed R-R Interval we finding HRV component HF,LF and VLF.The HF signals were obtained by adding the square of level D4 and D5. As well as the LF signal were obtained by adding the square of level D6 and D7 respectively. The VLF component corresponded to the detail signal at square of level D7. We find the resulting HRV component HF= .18 Hz, LF= .14Hz and VLF=.556Hz[16]

6. RESULT AND DISCUSSION

In order the finding the HRV component such as a VLF ,LF and HF first we find the ECG signal by using BIOPACK MP 100C module with Acknowledge DAQ software and a digital dyadic wavelet-based decomposition with orthogonal Daubechies wavelets has been used. This procedure has the advantage of compact support and a finite impulse response representation with quadratic mirror filters. A total of more then ten healthy subjects (21 - 34 years old) were studied. After ECG analysis the corresponding interbeat interval (i.e., the R-R interval) data sequence is then computed. For the purpose of wavelet analysis, the R-R sequence derived from each ECG signal is further converted into a discrete-time signal with samples at equally spaced times using a resampling scheme.

The dyadic decomposition has forced to choose a sampling frequency of 4.8 Hz and to take decomposition level, J = 8 in order to have the best possible correspondence between physiological subbands and resulting dyadic frequency bands. The resulting bands between the VLF = 0.01875 - 0.0600 Hz, LF = 0.0375 - 0.15 Hz, and HF = 0.015 - 0.60 Hz. The

DWT algorithm is implemented using the Daubechies compactly supported orthonormal wavelet transform method, with an order of 4. Since time localization of the filter is very important for dynamic analysis, arbitrarily long filters cannot be used. In general, clinical studies of cardiovascular signals are based on the estimated spectral power in different frequency bands, with less focus on the location of the spectral peaks within the frequency bands. To analyze time-variant changes in the modulation within each subband, we calculated the instantaneous power for the reconstructed detail signals as the sum of squares of the coefficients. Because of large sample-to-sample variation, the power of each wavelet- filtered component was smoothed using a moving average filter. Figure 4.11shows the wavelet analysis performed on a signal representing R-R tachogram in a normal subject (F/23) with the time evolution of VLF, LF and HF powers under normal sleeping state

The desirable requirements of successful application of wavelet analysis to HRV signals that events are well localized in time and exhibit morphologic and spectral variations within these localized events have been achieved. Objectively viewing the signal at different scales should provide meaningful new information.

7. RESULTS AND CONCLUSIONS

This study is intended to compare FFT with WT. Therefore, an appropriate method for the analysis of ECG symptoms is being investigated. The fact is that ECG signals are stagnant and using Fourier to modify small changes may not be noticeable and my analysis changes depending on the length of the data. Thus in spectral analysis, it can be said that WT is more suitable than Fourier transform. The reason for this success depends on the measurement and dynamic characteristics of the mother wavelet. Another advantage of wavelet conversion is 3D representation of signals such as amplitude, frequency and time. 3D representation is much easier in pathological conditions as epilepsy extraction using WT subspectral components can also be represented as shown in Figure3. In addition to the above statements we can say that WT is a new strategy and also WT has been upgraded depending on the Fourier transitional version. Namely WT uses FFT to add a time domain view.

8. CONCLUSIONS AND FUTURE SCOPE

Wavelet analysis methods have been widely used in the signal processing of biomedical signals . Also, wavelet analysis techniques appear to have robust theoretical properties allowing novel interpretation of RR interval series. In general, these methods represent the temporal characteristics of a signal by its spectral components in frequency domain. Being a powerful alternative for the analysis of nonstationary signals, whose spectral features are changing over the course of time, wavelet analysis is very important to analyze biological signals since most of the statistical characteristics of these signals are nonstationary. The results show that wavelet transforms are capable to estimate the evolution of spectrum of RR interval time series obtained by induced changes in heart rate balance. This transform works as a filter, and extracts time-dependent signals of a specific frequency band from the original signal. Thus, wavelet transform can decipher temporal and localized changes or the status of physiological signals, and effectively quantify time varying changes in HRV. The proposed method could be the start for future WT-based analysis of HRV aimed at prediction of various autonomic disorders, which might be useful for clinical use, both for prognosis and for subsequent treatment. The results obtained indicate the existence of significant variations in the strength of the different frequency bands among the different temporal intervals analyzed. In brief, this approach provides time evolution of sympathovagal balance, evaluation of subject steadiness, dynamic analysis, and effect of various activities on HRV indexes. This may improve the overall quality of the measures of the indexes of spontaneous heart rate variability.

Also, these results may prove to be useful for dynamic modeling of cardiovascular regulation for testing the authentication of new techniques for analysis purposes.

REFERENCE

[1] Dilbag Singh, Vinod Kumar t, M.P. S. Chawlat 1999 ‘’Wavelet Filter Evaluation For HRV Signal Processing ‘’

[2] C. Saritha, V. Sukanya, Y. Narasimha Murthy 2008 ‘’ ECG Signal Analysis Using Wavelet Transforms ‘’ Bulg. J. Phys. 35 68–77

[3] Eucas Ganiero , Marce Risk , Jamil F Sobh , Agustin Wamirez , J Philip Saul ’’ Heart Rate Variability Analysis Using Wavelet Transform’’

[4] D. Singh, K. Vinod, S. C. Saxena and K. K. Deepak 2005‘’ An Iimproved Windowing Technique For Heart Rate Variability Power Sspectrum Estimation ‘’ Journal of Medical Engineering & Technology, Vol. 29, No. 2 March/ Aprail 2005, 95 – 101

[5] Emran M. Tamil, Hafeezah Kamarudin, Rosli Salleh, M. Yamani , Idna Idris, Noorzaily M.Noor, Azmi Mohd Tamil '' Heartbeat Electrocardiogram (ECG) Signal Feature Extraction Using Discrete Wavelet Transforms (DWT)'' Faculty of Computer Science and Information Technology, University of Malaya, Kuala Lumpur, Malaysia

[6] Mikhled Alfaouri and Khaled Daqrouq ''ECG Signal Denoising By Wavelet Transform Thresholding'' American Journal of Applied Sciences 5 (3): 276-2

[7] M. A. Khayer and M. A. Haque 2004 '' ECG Peak Detection Using Wavelet Transform'' 3rd International Conference on Electrical & Computer Engineering ICECE 28- Dhaka, Bangladesh

[8] P. Ranjith , P.C. Baby , P. Joseph 2002 '' ECG Analysis Using Wavelet Transform: Application To Myocardial Lischemia Detection'' ITBM-RBM 24 p. 44–47

[9] Costin Cepisca, Cosmin Karl Banica 1997 '' Evaluations Of Interctions Between Frequency Bands Of The ECG Signal With Wavelet Transform'' POLITEHNICA University of Bucharest, Electrical Engineering Faculty, costin@wing.ro

[10] Metin Akay, Yasemin M. Akay, Peter Cheng, Hazel H. Szeto 1994 ''Time-frequency Analysis Of The Electrocortica Activity During Maturation Using Wavelet Transform'' Biol. Cybern. 71, 169-176 15 November (1994)

[11] M. Akin12002 '' Comparison of Wavelet Transform and FFT Methods in the Analysis of EEG Signals'' Journal of Medical Systems, Vol. 26, No. 3

[12] Mikhled Alfaouri and Khaled Daqrouq 2008 '' ECG Signal Denoising By Wavelet Transform Thresholding'' American Journal of Applied Sciences 5 (3): 276-281.

[13] Guidelines 1996 ''Heart rate variability Standards of measurement, physiological interpretation, and clinical use Task Force of The European Society of Cardiology and The North American Society of Pacing and Electrophysiology'' European Heart Journal 17, 354– 381

[14] Dilbag Singh, Vinod Kumar '' The Time Evolution of Frequency Componentsof Heart Rate Variability Using Wavelets ''

[15] Dilbag Singh, B. S. Saini, Vinod Kumar, and Kishore K. Deepak 2006 '' Time-Evolution of Cardiovascular Variability During Autonomic Function Tests in Physiological2006 Investigations 28th IEEE EMBS Annual International Conference New York City,

[16] C. Saritha, V. Sukanya, Y. Narasimha Murthy2008 '' ECG Signal Analysis Using Wavelet Transforms '' Bulg. J. Phys. 35 68–77

[17] Hsiao-Lungchan, Hui-Hsunhuang and Jiunn-Leelin 2001 '' Time-Frequency Analysis of Heart Rate Variability During Transient Segments'' Annals of Biomedical Engineering, Vol. 29, pp. 983–996

[18] Suleyman Bilgin Omer H. Çolakb,, Etem Koklukaya, Niyazi 2008 ''Efficient Solution For Frequency Band Decomposition Problem Using Wavelet Packet In HRV ''Digital Signal Processing 18 892–899

[19] Mohammad Fazle Azeem , Ahmad Banakar, , Vinod Kumar 2006 '' Comparative Study of Diff-erent Types of Wavelet Functions in Neural Network International Joint Conference on Neural Networks Sheraton Vancouver Wall Centre Hotel, Vancouver, BC, Canada July 16-21, 2006

[20] Aswini Kumar M.D "ECG- simplified."

[21] Braunwald E. (Editor), "Heart Disease: A Textbook of Cardiovascular Medicine, Fifth Edition", p.108, Philadelphia, W.B. Saunders Co., 1997.

[22] D. Shander and T. M. Doran "The clinical value of the ECG in noncardiac conditions." Chest 2004; 125(4):