HEART RATE VARIABILITY ANALYSIS: A REVIEW

[1]D Mahesh Kumar, [2] S C Prasannakumar, [3] B G Sudarshan, [4] D Jayadevappa,

[1]Asst. Professor, [4]Professor, Dept. of Inst. Tech., JSSATE, VTU, Karnataka, (India)

[2]Professor, Dept. of Inst. Tech., RVCE, VTU, Karnataka, (India)

[3]Associate professor/medical officer, RVCE, VTU, Karnataka, (India)

ABSTRACT

Biological signals are nonlinear and non periodic in nature. The signals show self-similarity in various scales of time. Heart rate variability is a noisy time series having self-similar and self affine characteristics. Its analysis is commonly used in accessing the autonomic nervous system of the human body and in diagnosing of cardiac status and other parameters related to ANS in both normal and pathological conditions. The last two decades have shown that there is significant relationship between the Autonomic nervous system (ANS) and cardiovascular mortality, including sudden cardiac death. Easy and non-invasive way to measure has popularized its use. Fractal dimension is one of the robust methods in characterizing complex time series. Non linear time series methods are meant for extracting invariant of the dynamics of system that is a unique characteristic of the system. Unlike Euclidean dimension, fractal dimension is a fractal number that is characteristic of the statistical property and dynamics of the EKG. This paper reviews various methods used for the analysis of HRV and comparing HRV parameters in variouspathological conditions.

Keywords: Heart Rate Variability (HRV), Fractal Dimension, Hurst Component, Autonomic Nervous System (ANS), FFT and Spectral Analysis.

I INTRODUCTION

HRV is a ECG signal useful for understanding the status of the Autonomic Nervous System (ANS). HRV reflects the heart's ability to adapt to the changing circumstances by detecting and fast responding to the unpredictable stimuli. HRV analysis has the ability to assess overall cardiac health and the state of the ANS responsible for regulating cardiac activity. A key advantage of HRV analysis is the ability to detect the early signs of development of pathological processes or the presence of a functional disorder which may not be revealed by the procedures of ordinary methods. Nirmal D.Thakur et al [1] proposed conventional predictors, which diminished HRV predicts both death and arrhythmic events with greater sensitivity and specificity.

Fractal analysis is an emerging tool in cardiovascular diagnostics. It is based on recent discovery that the heart rate time series exhibits statistical properties associated with the dynamics of the heart beat. From past 20 years it is witnessed the relationship between ANS and cardiovascular mortality including sudden death due to cardiac arrest. Numerous number of papers appeared in connection with HRV related cardio logical issues reiterate the significance of HRV in assessing the cardiac health. Tulen and Man in t'veld [2] have found that, HR, diastolic Blood Pressure (BP), mid-frequency band power of HR and systolic BP, and plasma adrenaline concentrations showed significant increase when changed from supine to sitting to standing posture. Viktor et al. [3] have studied the variation of HR spectrogram and breathing rates in lateral and supine body positions. Recently, new dynamic methods of HRV quantification have been used to uncover nonlinear fluctuations in HR that are not otherwise apparent. Several methods have been proposed: Lyapunov exponents [4], approximate entropy [5] and detrended fluctuation analysis (DFA) [6]. It is a valuable tool to investigate the sympathetic and parasympathetic function of the ANS. The most important application of HRV analysis is the surveillance of post infarction and diabetic patients. HRV gives information about the sympathetic-parasympathetic autonomic balance and thus about the risk for sudden cardiac death (SCD) in these patients.

Kovatchev et al. [7] have introduced the Sample Asymmetry Analysis (SAA) and illustrate its utility for assessment of HR characteristics occurring, early in the course of neonatal sepsis and systemic inflammatory response syndrome (SIRS). Cysarz et al. [8] have demonstrated that the binary symbolization of RR interval dynamics, which at first glance seems to be an enormous waste of information, gives an important key to a better understanding of normal heart period regularity. In this paper [9] detrending method to be used before heart rate variability analysis (HRV) is pressure. The method is based on smoothness priors approach and operates like a time varying finite-impulse response high pass filter. The main advantage is its simplicity, and then frequency response of the method is adjusted with a single parameter. For other purpose of HRV analysis one should make sure that the detrending does not lose any useful information from the lower frequency components. The aim of this study which presented in [10, 11] was to examine the effects of endurance training on heart rate recovery after exercise and cardiac ANS modulation in female marathon runners. They have chosen time and frequency domain analysis of HRV which have been proven to be a non-invasive technique capable of providing information on autonomic modulation of the sinus node. Spectral analysis was repeatedly performed within the selected segment of ECG R-R interval data using 256-point [12] Fast Fourier Transformation [FFT]. The power spectrums obtained from spectral analysis were defined as two components HF power and LF power. HF power showed almost entirely mediated by the vagal activity, whereas LF power reflects the mixed modulation of vagal and sympathetic activities. The ratio of LF power was considered to reflect the sympatho- vagal balance. Finally it states that, the female marathon runners indicated faster HR recovery after exercise and altered cardiac ANS modulation at rest when compared to untrained controls. Verlinde et al. [13] have compared the HRV of aerobic athletes with the controls and showed that the aerobic athletes have an increased power in all frequency bands. These results are in accordance with values obtained by spectral analysis using the Fourier transform, suggesting that wavelet analysis could be an appropriate tool to evaluate oscillating components in HRV.

A method for analyzing HRV signals using the wavelet transform was applied to obtain a time-scale representation for very low-frequency (VLF), low-frequency (LF) and high-frequency (HF) bands using the orthogonal multi-resolution pyramidal algorithm [14]. Results suggest that wavelet analysis provides useful information for the assessment of dynamic changes [15] and patterns of HRV during myocardial ischemia. Auto regressing modeling of the HRV signal power spectrum was achieved, as well as approximate entropy was calculated for comparison. The results show changes in the spectral and non-linear dynamics parameters of the HRV signals when wearing the energy patches compared to these values when wearing the placebo patches. Finally they conclude that, both during rest and after five minutes of exercise the energy patches enhanced the relaxation level as they reduced the LH/HF (low frequency and high frequency) component. This is a very desirable effect as a reduced sympatho-vagal balance during rest has an enhancing relaxation effect and during exercise has an enhancing activity effect [16] presents a computer program for advanced HRV analysis. The program calculates all commonly used time and frequency domain parameters, the non-linear Poincare plot, advanced spectrum estimation methods, detrending options. Heart rate control [17] is perturbed by alterations in neuro-autonomic function including various diseases like sudden cardiac death and so on; these conditions are associated with a loss of the normal fractal complexity of inter beat interval dynamics, such changes which may not be detectable using conventional statistics, can be quantified using new methods derived from "chaos theory".

There has been interest in modeling the electro genesis of the QRS complex using a fractal like conduction system, as well as for studying alterations in the frequency content of the normal QRS due to changes in His purkinje geometry or myocardial conduction. Slow conduction in the myocardial cells activated by such a fractal network can lead to "late potentials", or to selective attenuation of higher frequency content of the QRS simulating changes seen in ischemic coronary syndromes. Changes in the geometry of the branching conduction system may alter the frequency content of the QRS complexes, independent of any changes in myocardial conduction spectral analysis was used for analyzing the HRV. It is clear that heart rate fluctuations are primarily due to autonomic nervous system dynamics. From chaos theory's concept, in this paper highlight some of the aspects of the application of fractals to various cardiac physiologies. The fractals have been applied at two specific levels of cardiac function. Ventricular depolarization and heart rate regulation. We relate the self similar and irregular branching structures of the His-purkinje system to the dynamics of ventricular activation and to the resultant frequency spectrum of the QRS complex. Power spectral analysis of beat-to-beat HRV has provided a useful means of understanding the interplay between autonomic and cardiovascular functionality.

1.1 The Autonomic Nervous System

The autonomic nervous system has 2 division's namely sympathetic nervous system and parasympathetic nervous system. Sympathetic state occurs during the stress condition or due to cardiac diseases, which causes an increase in Heart rate by increase in the rate of pacemaker cells in the hearts sino-atrial node. Parasympathetic activity results from the functioning of allergic reactions internal organs and so on and decreasing the fire rate of pacemaker cells and the HR, providing a regulatory balance in physiological autonomic function. The separate rhythmic contributions from sympathetic and parasympathetic autonomic activity modulate the heart rate (RR) intervals of the QRS complex in the ECG at distinct frequencies.

1.2 HRV and Blood Pressure

A method to describe relationship between short-term BP fluctuations and Heart rate variability in resting subjects was analyzed in the frequency domain. Relationship between pressure and interval variability indicate the 10sec. variability which indicate in systolic pressure leads the interval variation by two or three beats. Several structural and functional alterations of the cardiovascular system that are frequently found in hypertensive individuals may increase their cardiovascular risk beyond that induced by the BP elevation alone.

1.3 HRV and Myocardial Infarction

The HRV decrease with the recent myocardial infarction the predominance of sympathetic activity and reduction in parasympathetic cardiac control has been found in patients with acute myocardial infarction. Despite the beneficial effects on clinical variables, exercise training did not markedly alter HRV indexes in subjects after myocardial infarction.

1.4 HRV and Nervous System

Disorders of the central and peripheral nervous system have effects on HRV. All normal cyclic changes in HR are reduced in the presence of severe brain damage and depression. The significance of HRV analysis in psychiatric disorders arises from the fact that one can easily detect a sympatho-vagal imbalance. It is proved that, in physically healthy depressed adults the HRV does not vary from healthy subjects.

1.5 HRV and Cardiac Arrhythmia

A complex system like cardio-vascular system cannot be linear in nature and by considering it as a nonlinear system, can lead to better understanding of the system dynamics. Recent studies have also stressed the importance of non-linear techniques to study HRV in issues related to both health and disease. The progress made in this field using measures of chaos has attracted the scientific community to apply these tools in studying physiological systems, and HRV is no exception. There have been several methods of estimating invariants from non-linear dynamical systems being reported in the literature. Recently Fell et al. [18] and Radhakrishna et al. [19] have tried the nonlinear analysis of ECG and HRV signals, respectively. Also, Paul et al. (2002) showed that coordinated mechanical activity in the heart during VF may be made visible in the surface ECG using wavelet transform. Owis et al. [20] have used nonlinear dynamical modeling in ECG arrhythmia detection and classification. Acharya et al. [21-24] have classified the HRV signals using nonlinear techniques, and artificial intelligence into different groups. Dingfie et al. have classified cardiac arrhythmia into six classes using autoregressive (AR) Modeling.

1.6 HRV in Diabetes

Diabetes can cause severe autonomic dysfunction and can be responsible for several disabling symptoms, including SCD. Although traditional measures of autonomic function are able to document the presence of neuropathy, in general they are only abnormal when there is severe symptomatology. Thus by the time changes in function were evident, the natural course of autonomic neuropathy was well established. HRV and SCD Ventricular tachy-arrhythmias represent a leading cause of SCD in the community.

1.7 HRV and Renal Failure

In patients with renal failure, autonomic function tests have been done [25], followed by HRV indices and spectral analysis of HR. Although autonomic function tests revealed predominant impairment of the PNS [25], spectral analysis exhibited a strong reduction in the HR power spectrum at all frequency ranges, both sympathetically and Para-sympathetically. The relationship between HRV parameters and electrolyte ion concentrations in both pre and post dialysis is quoted in paper [26, 27, 28].

1.8 HRV and Gender, age

It is proved that, the HRV depends on the age and sex also. The HRV was more in the physically active young and old women [29]. It was proved by Emese et al. [30] that the alert new born have lowers HR variation in the boys than in the case of girls. The HR variation for healthy subjects from 20 to 70 years was studied by Bonnemeir et al. and found that the HRV decreases with age and variation is more in the case of female than men.

1.9 HRV and Drugs

HRV can be used to quantify the effects of certain drugs on the ANS. Heart rate variability can be significantly influenced by various groups of drugs. The effects of beta-blockers and calcium channel blockers on the heart rate variability have been studied in post infarction and hypertensive patients. In normotensive adults, the beta-adrenergic blocker atenolol appears to augment vagally mediated fast fluctuations in HR [31]. Guzzetti et al. [32] studied the effect of atenolol in patients with essential hypertension. They found not only an increase in HF fluctuations, but also a decrease in the sympathetically mediated LF oscillations. This decrease in sympathetic activity was also noticed in post infarction patients using metoprolol and in patients with heart failure using acebutolol. Thus, beta-blockers are able to restore the sympathetic–parasympathetic balance in cardiovascular disease.

1.10 HRV and Smoking

Studies have shown that smokers have increased sympathetic and reduced vagal activity as measured by HRV analysis. Smoking reduces the HRV. One of the mechanisms by which smoking impairs the cardiovascular function is its effect on ANS control. Recently Zeskind and Gingras have shown that cigarette exposed fetuses have lower HRV and disrupted temporal organization of autonomic regulation before effects of parturition, postnatal adaptation, and possible nicotine withdrawal contributed to differences in infant neurobehavioral function. Also, it was proved that, the vagal modulation of the heart had blunted in heavy smokers, particularly during a parasympathetic maneuver. Blunted autonomic control of the heart may partly be associated with adverse event attributed to cigarette smoking.

1.11 HRV and Alcohol

HRV reduces with the acute ingestion of alcohol, suggesting sympathetic activation and/or parasympathetic withdrawal. Malpas et al. [33] have demonstrated vagal neuropathy in men with chronic alcohol dependence using 24 hrs HRV analyses.

1.12 HRV and Sleep

The results from Togo and Yamamoto [34] suggest that mechanism involving electroencephalographic resynchronization and/or conscious states of the brain are reflected in the fractal component of HRV. Compared to stages 2 and 4 non-REM sleep, the total spectrum power was significantly higher in REM sleep and its value gradually increased in the course of each REM cycle.

1.13 HRV in Infants

Investigations in the fetus and newborn have revealed that, during rapid eye movement (REM) sleep long-term variability (LTV) was increased and short-term variability (STV) decreased compared to during non- REM sleeps [35]. These differences between REM and non-REM sleep, were due to a shift in the vagal-sympathetic balance from a higher sympathetic tone during REM sleep to a higher vagal tone during non-REM sleep.

II METHODS FOR ANALYSIS OF HRV

2.1 Time Domain Analysis

Two types of HRV indices are distinguished in time domain analysis. Beat-to-beat or STV indices represent fast changes in HR. LTV indices are slower fluctuations (fewer than 6 min–1). Both types of indices are calculated from the RR intervals occurring in a chosen time window (usually between 0.5 and 5 min). From the original RR intervals, a number of parameters are calculated such as SDNN, SENN, SDSD, RMSSD, NN50 (%), and pNN50% can be used as time domain parameters.

2.1.1 Statistical Method

By using long-term recording (24h) more complex statistical time-domain [36] measures can be calculated. This can be divided into two classes those which are derived from (a) instantaneous heart rate, and (b) differences between NN intervals. The simplest variable to calculate is the standard deviation of the NN interval (SDNN), i.e. the square root of variance. Since variance is mathematically equal to total power of spectral analysis, SDNN reflects all the cyclic components responsible for variability in the period of recording [37].Total variance of HRV [38] increases with length of analyzed recorded in table 1. All these measurements of short-term variation estimate high frequency variations in heart rate and thus are highly correlated.

Table 1: Time domain HRV Parameters.

Parameter	Description
NN 50 count	No. of adjacent RR-intervals differing by more than 50 ms in entire ECG recording
pNN 50	NN 50 count divided by total number of all RR-intervals
MAX- MIN	Difference between shortest and longest RR-intervals
SDNN	Standard deviation of all RR-intervals
SDNN index	Mean of the standard deviations of all RR-intervals for 5min segments in the entire recordings
SDANN	Standard deviation of averages of all RR-intervals for all 5min segments in the entire recordings
RMSSD	Root mean square of the differences between adjacent RR-intervals
SDSD	Standard deviation of differences between adjacent RR-intervals
HRV index	Total number of all RR-intervals divided by amplitude of all RR-intervals

2.1.2 Analysis by Geometrical Method

Geometrical methods present RR intervals in geometric patterns and various approaches have been used to derive measures of HRV from them. The triangular index is a measure, where the length of RR intervals serves as the X-axis of the plot and the number of each RR interval length serves as the y-axis. The length of the base of the triangle is used and approximated by the main peak of the RR interval and Frequency distribution diagram. The triangular interpolation of NN interval histogram (TINN) is the baseline width of the distribution measured as a base of a triangle, approximating the NN interval distribution (the minimum of HRV).

2.1.3 Poincare Geometry

The Poincare plot is a technique taken from nonlinear dynamics and portrays the nature of RR interval fluctuations. It is a plot in which each RR interval plotted as a function of the previous RR interval. Poincare plot analysis is an emerging quantitative-visual technique, whereby the shape of the plot is categorized into functional classes that indicate the degree of the heart failure in a subject.

2.2 Frequency Domain Analysis

The time domain methods are computationally simple, but lack the ability to discriminate between sympathetic and para-sympathetic contributions of HRV. These studies of HRV employed the periodogram or fast Fourier transform (FFT) for power spectral density (PSD) estimation procedure consists of two steps. Given the data sequence x(n), 0 £ n £ N–1, the parameters of the method are estimated. Then from these estimates, the PSD estimate is computed. But these methods suffer from spectral leakage effects due to windowing. The spectral leakage leads to masking of weak signal that are present in the data. The parametric (model based) power spectrum estimation methods avoid the problem of leakage and provide better frequency resolution than nonparametric or classical method. AR method can be used for the analysis of frequency domain. In AR method, the estimation of AR parameters can be done easily by solving linear equations. In AR method, data can be modeled as output of a causal, all pole, discrete filter whose input is white noise. AR method of order p is expressed as the following Equation.

$$x(n) = -\sum_{k=1}^{p} a(k)x(n-k) + w(n) \tag{1}$$

The power spectrum of a Pth order AR process is

$$r1 = 2^{2H-1} - 1 \tag{2}$$

The Burg method results in high resolution and yields a stable AR model. Spectral analysis of HRV can be a powerful tool to assess ANS function. It is not only useful when studying the path physiologic processes in certain diseases but also may be used in daily clinical practice.

2.3 Nonlinear Method of Analysis

Recent developments in the theory of nonlinear dynamics have paved the way for analyzing signals generated from nonlinear living systems. It is now generally recognized that these nonlinear techniques are able to describe the processes generated by biological systems in a more effective way. The technique has been extended here to study the various stress conditions of cardiac system parameters like Hurst exponent and fractal dimension which needs to be estimated. There are few other methods like rescaled range analysis, relative dispersion analysis, correlation analysis and Fourier analysis which is explained below.

2.3.1 Relative Dispersion Analysis

In spatial statistics, the relative dispersion (RD) analysis compares the variance of a variable as the measurement resolution increases. The RD equals the standard deviation divided by the mean. In time series analysis, one starts by measuring, at the highest level of resolution, the variance of the signal over its whole time course.

$$RD = RDo\left[\frac{n}{n_0}\right]^{H-1} \tag{3}$$

2.3.2 Correlation Analysis

Van Beek et a1.derived an equation for the correlation between measurements in adjacent units from the assumption that RD diminishes by a factor of 2^{H-1} when two pieces (values in the time series) are Lumped together, or are averaged (the bin Size is doubled):

$$r1 = 2^{2H-1} - 1 \tag{4}$$

The correlations between neighboring pieces are independent of the piece size, which is the reciprocal (approximately) of the number of units into which a domain has been divided. Bassingthwaighte and Beyer extended the formula to the autocorrelation coefficients between pieces where a(k) are AR coefficients and w(n) is white noise of variance equal to σ2 AR (p) model can be characterized by AR parameters {a[1], a[2],..., a[p], σ2 }. The important aspect of the use of AR method is the selection of the order p. Much work has been done by various researchers on this problem and many experimental results have been given in literature such as the papers presented by Akaike. The order of the AR model p = 16 can be taken. An AR process, x(n), may be represented as the output of an all-pole filter, i.e., driven by unit variance white noise. The Burg method is used to get the AR model pas which are separated by n - 1 intervening pieces:

$$r_n = \frac{(n+1)^{2H}}{2} - \frac{n+1}{2} - \sum_{i=1}^{n-1}(n-i+1)r_i \tag{5}$$

From this, they derived an expression r_n, that is not recursive, for all n > 0, integer or non-integer:

$$r_n = \frac{1}{2}\left\{|n-1|^{2H} - 2|n|^{2H} + |n+1|^{2H}\right\} \tag{6}$$

In doing so, they rediscovered the relationship described by [39], shows its meaning and merit with respect to fractional Brownian motion. The relationship for H > 0.5 for large n goes asymptotically to a power law relationship.

$$\frac{r_n}{r_{n-1}} = \left(\frac{n}{n-1}\right)^{2H-2} \tag{7}$$

2.3.3 Fourier Analysis

The power spectrum (the square of the amplitude from the Fourier transform) of a pure fractional Brownian motion is known to be described by a power law

$$|A|^2 \approx \frac{1}{f^{\beta}} \quad (8)$$

Where |A| is the magnitude of the spectral density at frequency f.

2.3.4 Hurst Exponent (H)

The Hurst exponent is a measure that has been widely used to evaluate the self-similarity and correlation properties of fractional Brownian noise, the time series produced by a fractional (fractal) Gaussian process. Hurst exponent is used to evaluate the presence or absence of long-range dependence and its degree in a time series. However, a local trend (non-stationarities) is often present in physiological data and may compromise the ability of some methods to measure self-similarity. Hurst exponent is the measure of the smoothness of a fractal time series based on the asymptotic behavior of the rescaled range of the process. The Hurst exponent H is defined as,

$$H = E + 1 - CD \quad (9)$$

Here, E is the Euclidean dimension. For normal subjects, the FD is high due to the variation being chaotic. And for CHB and Ischemic/ dilated cardio-myopathy, this FD decreases because the RR variation is low. And for AF and SSS, this FD value falls further, because the RR variation becomes erratic or periodic respectively.

2.3.5 Fractal Dimension

The term ‘‘fractal’’ was first introduced by Hans E.schepers [40]. A fractal is a set of points that when looked at smaller scales, resembles the whole set. The concept of fractal dimension (FD) that refers to a non integer or fractional dimension originates from fractal geometry [41, 42]. The FD emerges to provide a measure of how much space an object occupies between Euclidean dimensions. The FD of a waveform represents a powerful tool for transient detection. This feature has been used in the analysis of ECG and EEG to identify and distinguish specific states of physiologic function. Many algorithms are available to determine the FD of the waveform. In this work, algorithms proposed by Higuchi and Katz are implemented for analysis of ECG and EEG signals.

2.4 Entropy Based Test

Entropy is a thermo-dynamical quantity that describes the amount of disorder in a system. This concept is studied by the Information item. This concept is studied by the Information theory, which was developed since 1940. This method provides to be an appropriate approach to temporal series analysis. The different entropy estimators are Approximate Entropy (AppEn), Sample Entropy (SampEn), Symbolic Entropy (SymEn), Multi Scale Entropy (MSE), Gaussian Entropy (GaussianEn). MSE and GaussEn are used for long term data where asAppEn, SampEn and SymbEn are used for short term data [6].Entropy based methods provide a quantification of the irregularity of a temporal series. The entropy concept is concerned with the uncertainty inherent in the signal i.e., with the amount of information it contains. The use of these methods to quantify data irregularity in cardiac signal is motivated by the meaningful differences founded with respect to the degree of irregularity on these signals depending on the health states, which reflects important physiological information.

III REQUIREMENTS FOR NON-LINEAR ANALYSIS

Specifics of the biological systems require modifications of standard nonlinear dynamic algorithms. The main problems of the nonlinear analysis [43], when applying it to biological signals can be summarized as follows: (a) high level of random noise in the biological data. The applied nonlinear dynamic methods should be robust to the noise influence; (b) short experimental data sets due to the low frequencies of the biological signals. Short realizations cause large error bars in the estimation of the chaos parameters; (c) non stationary of the biological systems, i.e., ECG, EEG have different modulations influenced by a various external factors with different characteristic times; (d) spatially extended character of the system.

IV EXTRACTION OF DATA

Electrocardiogram can be acquired by the help of electrodes called ECG leads. The ECG leads are attached to body of the subject in a specific pattern and location, namely Bi-polar leads (aVL, aVR, aVF), Uni-polar leads (lead I, Lead II, Lead III) and by Uni-polar pericardial leads. ECG electrodes are of different types based on their property of measurement and functionality, like disposable electrode (low cost, pericardial attachment), clip electrodes (for arm and leg connection).

Totally 12 leads are there to acquire ECG in which 9 are uni-polar (6 pericardial leads and 3 augmented leads) and 3 are bi-polar leads connected to left and right hand and to leg. This set up is used in the hospitals for complete acquisition of ECG signal, which is useful for clinical analysis.

For autonomic nervous system functioning experiment its sufficient to take 3-lead ECG (RA, LA & RL), to know heart rate using R-R interval. 3-lead ECG is taken from the subject (patient) by using clip electrode attached to right and left arm and to left leg. This ECG may contain power line interference and other motion artifacts, this can removed by using a notch filter and a band stop filter.

V SOFTWARE TOOLS TO ANALYZE HRV

There are various software tools to analyze the Heart Rate Variability, namely MATLAB, LabVIEW, and SciLab etc., and many other commercial software are also available [44]. MATLAB is a software programming tool used for the numerical analysis of the signals, image and voice etc., these properties makes MATLAB as most popular software tool to analyze various signals. MATLAB supports numerous functions which are helpful analysis of various type of signal. For the analysis of heart rate MATLAB provides better performance than the other tool which is available in market by providing a number of signal processing tools, which are helpful to analyze and display the signals with required parameters.

LabVIEW is software tool supports various types of hardware interfaces which are used for the signal extraction and for processing. LabVIEW programs are called virtual instruments, or Vis, because their appearance and operation imitate physical instruments, such as oscilloscopes and millimeters. LabVIEW contains a comprehensive set of tools for acquiring; analyzing, displaying, and storing data as well as tools to help for troubleshoot of code. In Lab View, it can build a user interface, or front panel, with controls and indicators. Controllers are input functions, and indicators are output functions. By building user interface initially, later code can be added to control the front panel objects. SciLab is free and open source software [45] for numerical computation providing a powerful computing environment for engineering and scientific applications. It is capable of interactive calculations as well as automation of computations through programming. The greatest features of Scilab are that it is multi-platform and is free. It is available for many operating systems including Windows, Linux and MacOS X.

VI UTILITY OF NEURAL NETWORK IN ANALYSIS OF HRV DATA

Heart Rate Variability has recently been shown as a viable index to predict sudden cardiac death. The use of neural network technique [46] to classify detected QRS complexes into normal and abnormal ones. A single layer perceptron neural network is used for this QRS pattern learning and classification [47]. Results with real data showed that the algorithm gives a 99% correct QRS detection rate.

VII CONCLUSION

Heart rate variability analysis has become an important tool in cardiology, because the measurements are noninvasive and easy to perform, have relatively good reproducibility and also provide prognostic information on patients with heart diseases. Linear & Nonlinear methods are used to analyze the health of the different subjects and it also helps in the early detection of disease. Pion-care Plot can be used for analysis of HRV. It has been studied widely.

REFERENCES

[1] Nirmal D.Thakur, Manoj S. Sankhe, K. D. Desai, *"Implementation of HRV system for understanding behavior of autonomous nervous system*", International Journal of Electronics and Computer Science Engineering, PP. 1197-1207.

[2] Tulen J H, Boomsma F, Man, *"Cardiovascular control and plasma catecholamines during restand mental stress: effects of posture",* Clinical Science (London), No. 96, PP. 567–576, 1999.

[3]. Viktor A, Jurij-MAtija K, Roman T , *"Breathing rates and heart rate spectrograms regarding body position in normal subjects".* Computer Biological Medicine, No.33, PP 259–266, 2003.

[4]. Rosenstien M, Colins JJ, De Luca CJ, *"A practical method for calculating largest Lyapunov exponents from small data sets"*. Physica D 65:117–134, 1993.

[5]. *S. M. Pincus*, "*Approximate entropy as a measure of system complexity*," *Proc. Natl. Acad. Sci. USA 88, 2297–2301*, 1991.

[6]. Peng CK, Havlin S, Hausdorf JM, Mietus JE, Stanley HE, Goldberger AL, "*Fractal mechanisms and heart rate dynamics",* J Electrocardiol 28(Suppl):59–64, 1996.

[7]. Kobayashi M,Musha T, *"1/f fluctuation of heart beat period",* IEEE Trans Biomed Eng 29:456–457, 1982.

[8] Cysarz D, Bettermann H, van Leeuwen P, *"Entropies of short binary sequences in heart period dynamics",* Am J Physiol Heart Circ Physiol 278:H2163–H2172, 2000.

[9]. Gregory Blain and Stephane Bermon,"*Influence of the pedalling frequency on the Heart Rate Variability",* Olivier Meste, member *IEEE*, PP. 279-282, 2007.

[10]. M.jeanne,R.logier,j.de jonckheere,B, *"Validation of a graphic measurement of heart rate variability to assess analgesia/nociception balance during general anesthesia",* Tavernier, PP. 1840-1843, 2009.

[11] Eleonora Tobaldini, Alberto Porta, Mara Bulgheroni, Marica Pecis, Milena Muratori, Maurizio Bevilacqua, Nicola Montano, '*Increased complexity of short-term HRV in hyperthyroid patients during orthostatic challenge'.* 30th Annual International IEEE EMBS Conference Vancouver, British Columbia, Canada, August 20-24, 2008.

[12] Ge D, Srinivasan N, Krishnan SM, *"Cardiac arrhythmia classification using autoregressive modeling",* BioMed Eng Online 1(1):5, 2002.

[13] Verlinde D, Beckers F, Ramaekers D, Aubert AE, *"Wavelet decomposition analysis of heart rate variability in aerobic athletes",* Auton Neurosci 90(1–2):138–141, 2001.

[14]. Gamero LG, Vila J, Palacios F, *"Wavelet transform analysis of heart rate variability during myocardial ischaemia",* Med Biol Eng Comput 40:72–78, 2002.

[15]. Eleonora Tobaldini, Alberto Porta, Mara Bulgheroni, Marica Pecis, Milena Muratori, Maurizio Bevil acqua, "*Increased Complexity of Short-Term Heart Rate Variability in Hyperthyroid Patients During Orthostatic Challenge ",* Nicola Montano, PP 1988-1991.

[16]. G. N. Arbolishvili, V. Y. Mareev, Y. A. Orlova, and Y. N. Belenkov, *"Heart rate variability in chronic heart failure and its role in prognosis of the disease,"* Kardiologiya, vol. 46, no. 12, pp. 4–11, 2006.

[17]. Homer Nazeran, Surya Chatlapalli, Rohit Krishnam, *"Effect of Novel Nanoscale Energy Patches on Spectral and Nonlinear Dynamic Features of Heart Rate Variability Signals in Healthy Individuals during Rest and Exercise",* Department of Electrical and Computer Engineering, The University of Texas at El Paso, El Paso Texas, USA School of Informatics and Engineering, Flinders University of South Australia, Adelaide, Australia PP 5563-5567.

[18]. Fell J, Mann K, Roschke J, Gopinathan MS, *"Nonlinear analysis of continuous ECG during sleep I. Reconstruction",* Biol Cybernat 82:477–483, 2000.

[19]. Radhakrishna Rao KA, Vikram Kumar Yergani, Narayana Dutt D, Vedavathy TS, "*Characterizing chaos in heart rate variability time series of panic disorder patients"*, In: Proceedings of ICBME Biovision. Bangalore, India, pp 163–167, 2001.

[20]. Owis MI, Abou-Zied AH, Youssef ABM, Kadah YM, *"Study of features on nonlinear dynamical modeling in ECG arrhythmia detection and classification",* IEEE Trans Biomed Eng 49(7):733–736, 2002.

[21]. Acharya UR, Min LC, Joseph P, "*HRV analysis using correlation dimension and DFA",* Innov Tech Biol Med (ITBM-RBM) 23:333–339, 2002.

[22]. Acharya UR, Bhat PS, Iyengar SS, Rao A, Dua S, "*Classification of heart rate using artificial neural network and fuzzy equivalence relation",* Pattern Recogn 36:61–68, 2003.

[23]. Acharya UR, Kannathal N, Krishnan S M, "*Comprehensive analysis of cardiac health using heart rate signals"*, Physiol Meas J 25:1130–1151, 2004.

[24]. Acharya UR, Kannathal N, Seng OW, Ping LY, Chua T, *"Heart rate analysis in normal subjects of various age groups",* Biomed Online J USA 3(24), 2004.

[25]. Zoccali C, Ciccarelli M, Maggiore Q, *"Defective reflex control of heart rate in dialysis patients: evidence for an afferent autonomic lesion"*, Clin Sci 63:285–292, 1982.

[26]. Axelrod S, Lishner M, Oz O, Bernheim J, Ravid M, *"Spectral analysis of fluctuations in heart rate: an objective evaluation of autonomic nervous control in chronic renal failure",* Nephron 45:202–206, 1987.

[27]. Tsai A C, Chiu H W, *"Relationship between heart rate variability and electrolyte concentration in chronic renal failure patients under hemodialysis",* Int J Bioelectromagn 4(2):307–308, 2002.

[28]. Ewing DJ, Winney R*, "Autonomic function in patients with chronic renal failure on intermittent haemodialysis",* Nephron 15(6):424–429, 1975.

[29]. U. Rajendra Acharya, K. Paul Joseph, N. Kannathal, Choo Min Lim & Jasjit S. Suri, *"Heart rate variability: a review"*, Medical and Biological Engineering, 2006.

[30]. Nagy E, Orvos H, Bardos G, Molnar P*, "Gender related heart rate differences in human neonates",* Pediatr Res 47(6):778–780, 2000.

[31]. Muller J E, Morrison J, Stone P H, Rude R E, Rosner B, Roberts R*, "Nifedipine therapy for patients with threatened and acute myocardial infarction:* a randomized, double-blind, *placebo-controlled comparison",* Circulation 69:740–747, 1984.

[32]. Guzzetti S, Piccaluga E, Casati R, Cerutti S, Lombardi F, Pagani M, *"Sympathetic predominance in essential hypertension: a study employing spectral analysis of heart rate variability",* J Hypertens 6:711–717, 1988.

[33]. Malpas S C, Whiteside E A, Maling T J, *"Heart rate variability and cardiac autonomic function in men with chronic alcohol dependence",* Br Heart J 65:84–88, 1991.

[34]. Togo F, Yamamoto Y, "*Decreased fractal component of human heart rate variability during non-REM sleep",* Am J Physiol Heart Circ Physiol 280:H17–H21, 2000.

[35]. Rother M, Zwiener U, Witte H, Eiselt M, Frenzel J, *"Objective characterization and differentiation of sleep states in healthy newborns and newborns-at-risk by spectral analysis of heart rate and respiration rhythms",* Acta Physiol Hung 71:383–393, 1988.

[36] WANG Xing , XU Liang , SUN Zhongwei , YANG Zibin, *"Heart rate variability analysis of ischemic and heart rate related ST-segment deviation episodes based on time-frequency method", Digital Object Identifier:* 10.1109/NFSI-ICFBI.2007.4387715,PP.162-164,2007.

[37] U. Rajendra Acharya, K. Paul Joseph, N. Kannathal, Choo Min Lim, Jasjit S. Suri, *"Heart rate variability: a review",* Med Bio Eng Comput No.44:1031–1051, 2006.

[38] L. Pecchia, P. Melillo,M. Sansone, and M. Bracale, *"Heart rate variability in healthy people compared with patients with congestive heart failure,"* in Proc. 9th Int. Conf. Inform. Technol. Appl. Biomed., Larnaca, Cyprus, 2009, pp. 1–4.

[39] Olivier Meste, Gregory Blain and Stephane Bermon, "*Influence of the pedaling frequency on the heart rate variability",* Proceedings of the 29th Annual International Conference of the IEEE EMBS Cité Internationale, Lyon, France, August 23-26, 2007**.**

[40]. Hans E. Schepers , H.G.M. van Beek, *"Four Methods to Estimate the Fractal Dimension from Self-Affine Signals",* IEEE, Eng. Med. Biol. Mag., 11(2), PP. 57-64, 2002.

[41] Elisa Hemmig Maturarbeit, *"Fractal analysis of heart rate variability in patients following surgical repair of acute type of A Aortic Dissection",* Gymnasium Liestal, 2007/2008.

[42] J. L. Hernández Cáceres , H. Foyaca Sibat, R. Hong, M. Sautié, A. V. Namugowa, *"Towards the estimation of the fractal dimension of heart rate variability data",* The Internet Journal of Cardiovascular Research, Volume 2 Number 1, 2005.

[43] Maide Bucolo, *'Mapping heart dynamics by using non-linear indicators'.* Proceedings of the 29th Annual International Conference of the IEEE EMBS Cité Internationale, Lyon, France, PP 23-26, 2007.

[44]. Juha-Pekka Niskanen, Mika P. Tarvainen, Perttu O. Ranta-aho, and Pasi A. Karjalainen, ***"S****oftware for advanced HRV analysis". University of Kuopio Department of Applied Physics Report* Series ISSN 0788-4672, 2002.

[45] Juha-Pekka Niskanen, Mika P. Tarvainen, *"Software for advanced HRV analysis",* University of Kuopio Department of Applied Physics Report Series ISSN 0788-4672.

[46] R.U. Acharya, A. Kumar, P.S. Bhat, C.M.Lim, S.S.
Iyengar , N. Kannathal,and S.M. Krishnan,*"Classification of cardiac abnormalities using heart rate signals," Med.Biol.Eng.Comp.*, vol.42, pp.288-293, 2004.

[47] D. Ubeyli, *Adaptive neuro-fuzzy inference system for classification of ECG signals using Lyapunov exponents, Computer Methods and Programs in Biomedicine,* Elsevier.

AUTHORS

D. Maheshkumar. He completed B.E in Instrumentation Technology & M.Tech. in Bio-Medical Instrumentation from Sri Jayachamarajendra College of Engineering, Mysore. He has 16 years of teaching experience and he also pursuing Ph.D from Jain University, Bangalore,Karnataka. Currently he is working as Assistant Professor in the dept. of Inst. Technology, JSSATE, Bangalore. His areas of interest are Biomedical Signal processing, Electronic Instrumentation and Smart Sensors. He is the member of ISOI and ISTE.

Dr. S C Prasannakumar. He received his B.E & M. Tech. degree from Jayachamarajendra College of Engg. Mysore, and completed Ph.D degree from Avinash Lingam University, Tamilnadu, India. He is currently working as Professor in the department of Instrumentation Technology, RVCE, Bangalore. He has 17 years of teaching and industrial experience and he is the Member of ISTE. His areas of interests are Signal Processing (Acoustic Signal Processing) & Bio-Medical Instrumentation. He is the BOS & BOE of VTU and autonomous institutes. He has more than 28 publications in International & National Journals and also in conferences.

Dr. B G Sudarshan. He received MBBS degree from Sree Siddaratha Medical College, Tumkur and Ph.D in Bio-Medical Instrumentation from Avinash Lingam University, Tamilnadu. Currently he is working as Associate professor/medical officer at RVCE IT hospital and also Faculty in the dept. of Inst. Tech. He has more than 10 publications in International and National Journals & also in conferences. He has more than 9 years of experience in this field and his area of interest are Bio-medical signal processing and Image processing.

Dr. D Jayadevappa. He received his B.E degree in Instrumentation Technology from Siddaganga Institute of Technology, Tumkur, Bangalore University in 1994, M.Tech degree from Jayachamarajendra College of Engineering, Mysore, Visveswaraya Technological University in 2000 with specialization in Bio-Medical Instrumentation and completed Ph.D degree from JNTU college of Engineering, A.P, India. He is currently working as Professor in the department of Instrumentation Technology, JSSATE, Bangalore. He has 18 years of teaching and industrial experience and he is the Member of BMESI, IAENG, IETE, and ISTE. He has published 17 papers in various International & National Journals and also in conferences .He is the reviewer of IETE technical review and British Journal of Biomedical Engineering. His areas of interests are Digital Image Processing and Bio-Medical Signal Processing.