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A Study on Heart Rate Variability Using Time and Frequency Domain

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ABSTRACT

Heart rate variability (HRV) is a measure of the balance between sympathetic mediators of heart rate that is the effect of epinephrine and norepinephrine released from sympathetic nerve fibres. Heart Rate (HR) is a non-stationary signal. They provide a powerful means of observing the interplay between sympathetic and parasympathetic nervous system. In this paper, we reviewed that Heart Rate Variability becomes an important characteristic to determine the condition of heart. That's why the calculation of HRV is necessary. ECG is used to detect the heartbeat. ECG signal contains lots of noise. To classify the signals first to decompose the signals using wavelet transform. Support Vector Machine is used to classify the denoise signal and for better classification of ECG signal. This paper gives Brief Survey on different technique and Wavelet Transform for better Feature Extraction of ECG signals. Study of HRV enhance our understanding of physiological phenomenon, the actions of medications and disease mechanisms but large scale prospective studies are needed to determine the sensitivity, specificity and predictive values of heart rate variability.

Keywords : ECG, Heart rate variability, SVM Classifier, k-means clustering, discrete wavelet transform, fourier transform, feature extraction.

I. INTRODUCTION

Heart Rate Variability (HRV) is a physiological phenomenon defined as variation in RR intervals (RRI) during normal sinus rhythm. The RRI is defined as the time interval between adjacent QRS complexes resulting from sinus node depolarization. Since the sinus node is subject to both sympathetic and parasympathetic efferent effects, the fluctuations of the RRI have been well accepted to reflect the effects of the autonomic nervous system [2]. The measurement of HRV is non-invasive, often reproducible and rather easy to perform and has led to its popularity as a method for the measurement of autonomic tone in varying physiological and pathological states.

Traditional methods of HRV analysis, often referred to as linear methods, include time and frequency domain analysis. Time domain analyses of HRV are usually obtained using simple statistical methods. The simplest time domain parameter is the mean of the RRI (RR mean), which is the average RRI over a given time window. Another parameter commonly used is the standard deviation of the RRI (SDNN) which is sometimes regarded as an estimate of overall HRV.

Other measures include RMSSD, the square root of the mean squared differences of successive NN intervals, NN50, the number of interval differences of successive NN intervals greater than 50 ms, and pNN50, the proportion derived by dividing NN50 by the total number of NN intervals. All these are based on differences between RR intervals and thus are highly correlated, and they all estimate the short-term components of HRV.

II. METHODS AND MATERIAL

Methods Used To Classify HRV

2.1. Time-domain HRV measures

The derivation of standard time-domain HRV measures is quite simple. Time domain measures are calculated from HRV data. These measures are Mean (mean of all RR intervals), SDNN (standard deviation of all RR intervals) [2].

2.2. Frequency-domain HRV measures

These are based power spectral density (PSD) analysis of the HRV data. The power spectral can be obtained using FFT or wavelet based measures including variances, energies, and entropies. Some pre-processing steps such as interpolation and detrending are necessary depending on the algorithm used. In FFT-and wavelet-based algorithms is necessary to produce an evenly sampled time series from the HRV data, which are unevenly sampled form [30]. The spectral measures have the advantage of relating the power of variation in different frequency bands to different physiologically modulating effects. Three main spectral components are distinguished in a spectrum calculated from short-term HRV recordings: very-low-frequency (VLF), low-frequency (LF),and high-frequency (HF) components [24]. These frequency bands are bounded with the limits of 0-0.04 Hz, 0.04-0.15 Hz, and 0.15-0.40 Hz, respectively.

2.3. DWT for Feature Extraction

Fourier Transform is used to provide only frequency domain information and poor time resolution for any signal [7]. To provide good signals having same frequency at different times have same Fourier magnitude due to high frequency resolution and low time resolution. To overcome this issue Wavelet transform provides multi resolution analysis. To decompose the ECG signal into time frequency several mother wavelet used such as Haar, DB, Coieflet, Symlet, and Mexican Hat.

Researchers uses many mother wavelet for better results among them DB series i.e. Db2 to Db45 which has similar shape as ECG signal. The decomposition is done up to many levels such as level 1 to level 4 for smoothness of signals [9]. Wavelet transform provides better features extraction and also give more relevant features for better discrimination in ECG signal analysis. Many Researchers also works on non-linear features. For non-linear feature extraction Polynomial Kernel from support Vector Machine is used which shows good heart beat classification [4].

2.4. Feature Selection

The main purpose of the feature selection is determining the feature subset which gives the highest discrimination between the groups. Using all features in a classifier does not give the best performance in many cases [13]. Feature selection also helps people to acquire a better understanding about which features are important in diagnosing the data of interest.

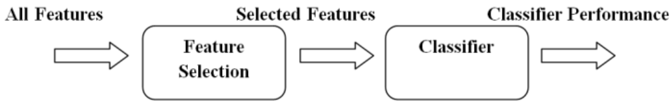

Figure 1. Feature selection algorithms based on the filter approaches [13].

2.5. Classification

In this study, k-means clustering, Linear Discriminant Analysis (LDA), Multi-Layer Perceptron (MLP), Support Vector machine (SVM),and Radial Basis Functions (RBF) were used for the pattern classification.

2.5.1. K-means clustering

K-means clustering is a partitioning method. The function k-means partitions data into k mutually exclusive clusters, and returns the index of the cluster to which it has assigned each observation. Unlike hierarchical clustering, k-means clustering operates on actual observations (rather than the larger set of dissimilarity measures), and creates a single level of clusters. The distinctions mean that k-means clustering is often more suitable than hierarchical clustering for large amounts of data [2].

2.5.2 Linear discriminant analysis (LDA)

It is a popular method for both the size reduction and the classification [8, 9]. It is a statistical method that maximizes the ratio of between-class to within-class scatter matrices. It seeks a projection to reduce dimensionality while preserving as much of the class discriminatory information as possible. Euclidean distances between test data and classes means of the projected data are calculated. Then the classes of test data are obtained by considering the minimum distances.

2.5.3. Multi-layer perceptron (MLP)

MLP is a popular method to model linear and non-linear relationship between inputs and outputs among artificial neural network structures. It is frequently used in the diagnosis of several diseases [8–9]. MLP has a three-layer structure in general. The number of neurons in the hidden layer is set to all integers between1and50.The activation function of neurons in this layer is the function of “tanh”. The output layer computes the final response of the network with the activation function of “linear”.

2.5.4. Supportvectormachines (SVM)

It is used in many applications both classification and the regression of linear and non- linear data [15]. The main purpose is to predict the decision-making function to separate two classes by moving data to a hyper-plane.There may be several hyperplanes. SVM is aimed to find the optimal hyper-plane that maximizes the distance between adjacent points of both classes. Selected data points are called support vectors that define the limits of hyper-plane.

2.5.5. Radial basis function (RBF)

RBF is artificial neural network architecture. Transformation between the input layer and the hidden is non-linear; on the other hand, that of between the hidden layer and the output layer is linear. The activation function of neurons in the hidden layer is radial basis (generallyGaussian) [13].The learning consists of two steps :unsupervised learning method to estimate the center of the basis function and supervised learning method to adjust network weights between the hidden layer and the output layer.

2.5.6. Accuracyandperformancemeasures:

The performance of the classifier is determined by sensitivity (SEN), specificity (SPE). SEN is the ratio of the number of positive decisions correctly made by the recognition system to the total number of positive decisions made by the expert. SPE is the ratio of the number of negative decisions correctly made by the recognition system [13].

III. RESULT AND DISCUSSION

Comparison of Results

Table 1: Review of Various Papers on analysis &classification of heart rate variability using time-frequency domain

Authors& Year	Paper Title	Methods used	Classifier used	Result
Anju M. Rao et al. [2002]	Classification of HRV parameters by receiver operating characteristics	QRS Peak Detection, Time domain analysis, Frequency domain analysis, Statistical analysis	-	Area under the ROC curve indices SDRR, SDARR classify abnormal from normal patient.
Joao Luiz et al. [2002]	Development of matlab software for analysis of HRV	QRS detection module, Time analysis module-pNN50,RMSSD,Spectral analysis module, Pointcare analysis module	-	Software obtains the HRV signal by using QRS detection system.
Tran Thong et al. [2003]	Accuracy of ultra-short heart rate variability measures	HRV time domain measure-statistical measures, geometric measures	-	Accuracy of HRV measures-73.91%
Oliver Faust et	Analysis of cardiac	Spatial filling index,	-	Spatial filling index,

al. [2004]	signals using spatial index and time-frequency domain	Time-Frequency analysis, Wignerville analysis, CWT, Renyi's entropy.		Renyi's entropy gives an accuracy of 95% for various diseases
Chia-Hung Lin [2007]	Frequency domain features for ECG beat discrimination using grey relational analysis-based classifier	Mathematical method, Frequency domain characteristics-feature extraction, comparative sequence creation	GRA-based classifier	GRA based classifier uses frequency features to identify the cardiac arrhythmias.
Elias Ebrahimzadeh et al. [2011]	Early detection of sudden cardiac death by using linear techniques and time-frequency methods.	Time domain features, Frequency domain features, Feature dimension reduction	MLP,KNN	MLP accuracy-67.42% KNN accuracy-68.54%
Xi Long et al. [2012]	Time-Frequency analysis of HRV for sleep and wake classification	HRV spectrum, Time frequency analysis, HRV feature extraction.	-	Sensitivity-50.6% Specificity-93% Accuracy-89%
Ali Narin et al. [2013]	Investigating the performance improvement of HRV indices in CHF using feature selection method	Time domain measures-mean of RR intervals, Frequency domain measures, Non-linear measures.	KNN,LDA, MLP,SVM, RBF	Sensitivity-82.75% Specificity-96.29% Accuracy-91.56%
Veena N.Hegde et al. [2013]	HRV analysis for abnormality detection using time-frequency distribution	SPWVD method for time frequency analysis.	-	HF and LF Component position indicating abnormality of the heart.
Faizal Mahananto et al. [2013]	Cardiac arrhythmia detection using combination of HRV analyses and PUCK analysis.	HRV analysis-time domain, frequency domain, Non-linear analysis	PUCK(Potential of unbalanced complex kinetics)	Time domain accuracy-92% Frequency domain accuracy-80.26% Non-linear measure accuracy-90% PUCK accuracy-79%
Anna M. Bianchi et al. [2013]	Methods of HRV analysis during sleep	Spectral and cross-spectral analysis, Time-Frequency analysis, Long term correlation analysis, DFA	-	Time-Frequency parameter measure the regularity and complexity of HRV signal acquired during the night.

Beatriz F Giraldo et al. [2013]	Analysis of HRV in elderly patients with chronic heart failure during periodic breathing.	Signal preprocessing, time domain, frequency domain measures, kolmogrov-smirnov test	-	Frequency domain parameters were most discriminant in comparison of patient with or without CHF.
Mika P. Tarvainen et al. [2014]	Kubios HRV–Heart Rate Variability Analysis software	QRS detection algorithm, Time domain features, Frequency domain, & non-linear methods.	Kubios HRV method	Kubios software computes all time domain or frequency domain parameters.
M.G Poddar et al. [2015]	Analysis and classification of HRV of healthy subjects in different age groups.	Linear method, Non-linear method, PCA based feature space dimension reduction.	KNN,SVM ,PNN	SVM accuracy-57.67% KNN accuracy-63.33% PNN accuracy-60%
Butta Singh& Nisha Bharti [2015]	Software tools for heart rate variability analysis.	Time domain features, Frequency domain, time-frequency & non- linear methods.	-	Kubois software analyse HRV in time, frequency, non-linear measures
In cheol Jeong et al. [2015]	Comparative utility of time and frequency HRV domains for classification of exercise exertion levels.	System and data acquisition, time domain parameters-mean, standard deviation of RR intervals, Spectral estimation method	Discriminant analysis classifier	Time domain parameter accuracy-95.6% Frequency domain parameter accuracy-82.2%.
Mazhar B.Tayel et al. [2013]	Robustive& Sensitive method lynapunov exponent for heart rate variability.	Components of heart rate, Heart rate measures, lynapunov exponent.	Wolf's algorithm,Rosenstein algorithm.	Accuracy of wolf's method-65% Accuracy of Rosenstein method-79%
Manjit Singh et al. [2014]	Effect of ECG sampling frequency on approximate entropy base HRV.	Entropy measures of HRV-Approximate entropy (ApEn).	-	ApEn is used to measure the irregularity of a RR interval time series.
Dipali H. Patil et al. [2015]	Stress detection using heart rate variability.	Time domain analysis, Frequency domain analysis, Geometric method.	-	Sensitivity-77% Specificity-98%
N. Kumaravel et al. [2015]	Non- linear filters for preprocessing for heart rate variability signals.	Non- linear filtering, Adaptive rank order filters.	-	Adaptive non- linear filter is used to denoising the HRV signal.
Anilesh Dey et al. [2015]	Study the effect of music on HRV impulse using	Acquisition of HRV data, 2-D pointcare plot, DFA (Detrended fluctuation	-	DFA analysis is used to distinguish between pre-music & on-music state

	multifractal DFA Analysis.	analysis).		of normal healthy subjects.
Mazhar B. Tayel et al. [2016]	Novel reliable method assess HRV for heart disease diagnosis using bipolar MVF algorithm.	New (Mazhar-Eslam) approach, Bipolar MVF algorithm.	-	Sensitivity dependence of MVF algorithm-87%

IV. CONCLUSION

The analysis of HRV both by time-domain and frequency domain offer a non-invasive method of evaluating cardiac functioning.Heart Rate Variability (HRV) play an important role in monitoring, predicting, and diagnosing cardiological and non-cardiological diseases. In this paper, we present a review of different technique for classification heart rate variability for ECG data analysis. It shows that wavelet transform and support vector machine (SVM), linear discriminant analysis gives better results for HRV signal analysis.

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