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Survey on the Methods for Detecting Arrhythmias Using Heart Rate Signals

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Abstract:
The electrical activity of heart is symbolized with the help of ECG signal. This ECG signal is characterized by different peaks P, QRS, T and U that occur periodically at a particular interval of time. The occurrence of the peaks can also be represented as PR interval, QRS complex, QT interval, PR segment, ST segment. The amplitude and time interval of these peaks have specified normal range values. When these values differ from the specified values, the heart rate signal becomes abnormal. There are different abnormalities classified based on these values of the peaks in the ECG signal, which are extracted as features using mathematical models. In particular these abnormal signals are presented as arrhythmia signals which are a high threat to humans. The abnormal or irregular heart rate signal is termed as arrhythmia. The features extracted thus will define the character of each signal and are being used in the classification further. This paper reviews different methods of feature extraction and classification of both normal and abnormal ECG signals.

Keywords: QRS complex, feature extraction, arrhythmia.

1. INTRODUCTION

In recent years, diagnosis and treatment of various forms of diseases in human beings are becoming a major area in research. Diagnosis of biological malfunctions can be detected by various signals, which are obtained as electrical activity from the different parts of the human body. These electrical signals exhibit the normal and abnormal activities of those parts from which they are obtained. These signals are then being processed using different methods and classified based on the information obtained from them. In this paper, the activity and processing of ECG signal is discussed. ECG signal, which is the major representative of the function of heart, is the reflex of the electrical activity of heart. Researchers have ended up with many effective and novel algorithms in analyzing and classifying the ECG signal. The development of more and more efficient techniques leads to the better understanding of the ECG signal, which is considered as the major phenomenon in diagnosis of diseases. ECG signal is basically represented as P, QRS, and T waves. The figure below represents the ECG signal (Figure 1).

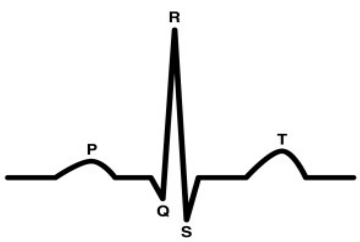

Figure 1. Representation of an ECG signal.

Each wave represent a particular event in the functioning of heart. Of these waves QRS complex, which is the major part of the ECG signal, indicates life threatening diseases which may also lead to mortality. These life threatening diseses which are termed as arrhythmia are detected from the R peaks present in the ECG signal. Hence the R peaks from the ECG signal are extracted and are represented as Heart Rate Variability signal or HRV signal. For easier computation these extracted signals are also used for the analysis of the normal as well as abnormal signals.

2. PROCESSING THE DATA

Data processing depends on the form in which the data for analysis is considered. These datas can be taken as 1D, 2D, 3D,… M-D signals, with any number of degrees of freedom. When the degrees of freedom increases, the number of data to be analysed increases and thus makes the process complicated. The algorithms through which the problem is solved for datas with higher degrees of freedom is more complex. 1D signals are in the form of waveform which are cansidered as a single variable, varying in terms of two axes variables. The processing of these signals and the development of problem solving algorithms are more easier and flexible. Whereas 2D, 3D, and other signals with higher degrees of freedom has many variables and are more complex to proceed mathematically. Hence 1D signals are considered in this paper to survey the simpler methods of analysing the ECG data. The process of data includes, the acquisition, storage, transmission and representation of the ECG signal as a 1D data.

3. METHODS USED FOR ANALYSIS

Analysis of ECG data includes the disintegration of the variables into simpler components for further processing. The disintegration is done by statistical methods for formulating the signal under consideration. In the papers reviewed in this survey, the signals for the process is obtained from MIT-BIH database [65,66]. Both normal and arrhythmia signals are obtained from the same database.
The preprocessing of the signals includes the baseline wandering removal and basic artifacts removal. The noiseless signal is then processed through any windowing technique such as thresholding window, hamming window, spline window, etc., to obtain the QRS complexes from the ECG signal. The obtained heart rate variability signal contains information about the heart rate occuring in the

signal obsereved. The heart rate and the interval between consecutive R peak differes with normal and arrhythmia signals. The convergence of these values from the normal signal are statistically formulated through various parameters. These parameters are either taken as such as inputs to the classifier or reduced in dimension and then given to the classifier. The flow diagram below depicts the steps through which the survey has been made through.

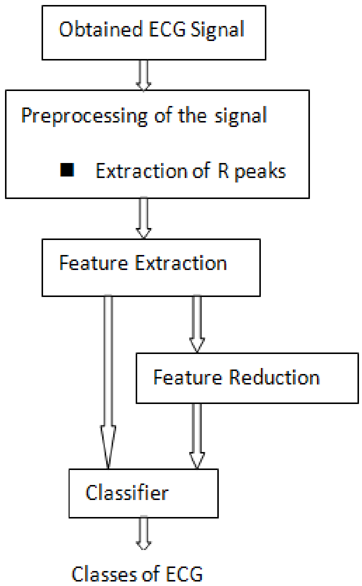

Figure 2 .Flow Diagram for the survey

According to the survey, there are many parameters that are extracted to define the characteristics of the signal under consideration. As mentioned already in this paper, the ECG signals, both normal and abnormal are obtained from the existing MIT-BIH database. These signals are preprocessed for noise removal and are tuned for the required frequency. The R peaks are then obtained using any form of efficient windowing techniques if required. The extracted heart rate variability signal or the ECG signal itself is used for further signal processing.

The ECG signal being used directly or the HRV signal extracted for reducing complexity in the signal is then processed in the following steps shown in the block diagram below (Figure 2) to obtain the required efficiency in classification of signals.

The steps include:

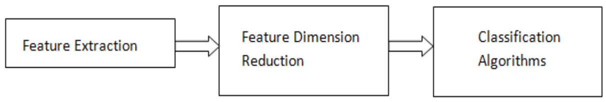

Figure 3 .Block diagram of the survey

The blocks mentioned above are explained clearly according to the review made through different papers in literature in the following sections.

3.1 Feature Extraction:

The bio signals for which the classification is to be made constitutes of large processing data. In order to reduce the complexity and increase the processing speed, the signals are made into simpler form of data using mathematical modeling. Measurement of features from HRV signal or ECG signal is done by considering linear and non linear methods.

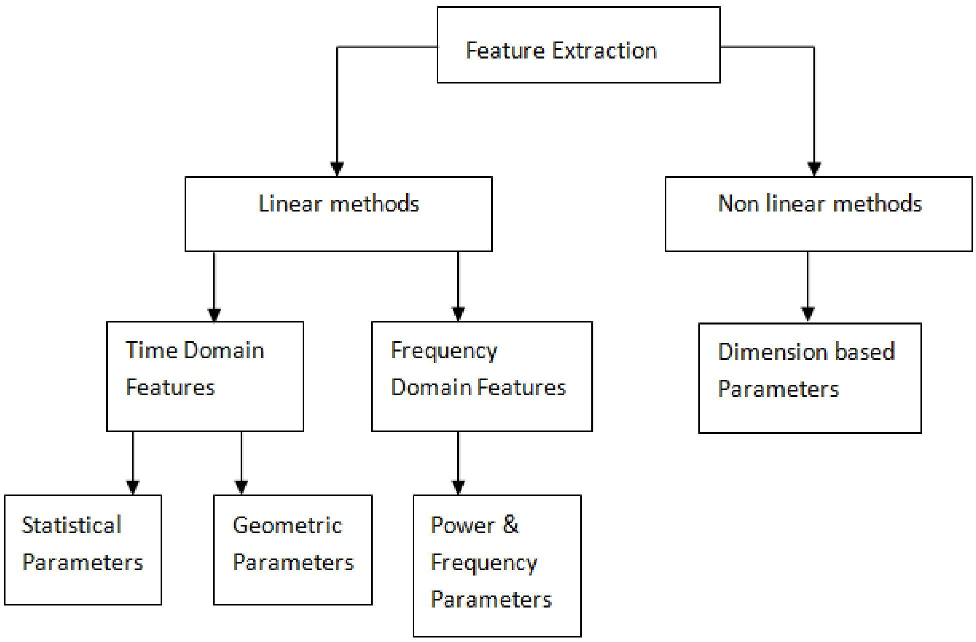

Figure 4 .Block diagram of Feature Extraction

Table 1 .List of time domain features - statistical

S.No	Feature	Description
1.	SDNN (ms)	The standard deviation of all peak to peak intervals [2, 3, 11, 12, 13, 16, 25, 34]
2.	SDANN (ms)	The standard deviation of the averages of peak to peak intervals in all specific segments of the full ECG signal under consideration [3, 11]
3.	RMSSD (ms)	The square root of the mean of the sum of the squares of differences between adjacent peak to peak intervals [2, 3, 11, 12, 16, 25, 34, 39]
4.	SDNN index (ms)	Mean standard deviations of all peak to peak intervals in all specific segments of the full ECG signal under consideration [3, 11]
5.	SDSD (ms)	Standard deviation of differences between adjacent peak to peak intervals [3, 11, 12, 16]
6.	NN50 count	Number of pairs of adjacent peak to peak intervals differing by more than 50ms in the entire recording [3, 39]
7.	pNN50 (%)	NN50 count divided by the total number of all peak to peak intervals [2, 3, 11, 12, 14, 16, 34, 39]
8.	pNN20 (%)	NN50 count divided by the total number of all peak to peak intervals [25, 34]
9.	Mean HR	Mean value of the heart rate measured [5, 14, 16, 39]
10.	Standard HR	Standard deviation of the measured heart rate [14, 39]
11.	RR mean	Peak to peak intervals are otherwise indicated as RR intervals. The mean of these interval values are also considered as useful measures [39]
12.	RR standard	Standard deviation of the RR intervals [39]

Table 2 .List of time domain features - geometrical

S.No	Feature	Description
1.	HRV triangular index or triangular index(TI)	The integral of the density distribution (that is, the number of all peak to peak intervals) divided by the maximum of the density distribution [3, 11, 14, 25, 34, 39]
2.	TINN	The triangular interpolation of NN interval or peak to peak histogram (TINN) is the baseline width of the distribution measured as a base of a triangle approximating the NN interval distribution [3, 11, 39]
3.	Differential Index	The difference between the widths of histogram of differences between adjacent peak to peak intervals measured at selected heights [3].
4.	Logarithmic Index	Best approximation of the histogram of absolute differences between adjacent peak to peak intervals [3].

Table 3 .List of frequency domain features

S.No	Feature	Description
1.	VLF	Power of Very Low Frequency range obtained from the power spectrum of the signal [34, 39].
2.	LF	Power of Low Frequency range obtained from the power spectrum of the signal [2, 13, 14, 34, 37, 39].
3.	HF	Power of High Frequency range obtained from the power spectrum of the signal [2, 13, 14, 34, 37, 39].
4.	LF/HF	Ratio of the Power of Low frequency range to that of High frequency range [2, 14, 16, 34, 37].

Linear methods comprises of two basic domains, Time domain and Frequency domain [1]. There are many number of time domain and frequency domain features.

Linear Methods:

Time domain Features:

The time domain measures include the information on the heart rate at any point of time interval. The standard deviation values are the most commonly used measure to evaluate the signal. NN interval is the time interval between one R peak and the other R peak. For a normal ECG signal, the amplitude and time interval for the occurrence of R peak at each sequence will be almost similar. Hence for a normal signal, the standard deviation value which is the deviation from the mean differs widely when the same is obtained for arrhythmia signals. The difference is because the amplitude and the time interval in an arrhythmia signal has different amplitudes in the R peaks and also differs in the time interval throughout the signal. Standard deviation is obtained in different forms such as SDNN which is the standard deviation of NN intervals, SDANN which is the deviation of the average value of NN intervals, SDNN index which is the mean standard deviation of all NN in a signal and other forms may include SDSD, standard Heart rate, RR standard, which are measured in terms of milliseconds (ms). Time domain features also include the proportional percentage values of the NN intervals at various time durations. The clear description of these features is given in the Table 1.

Geometrical measures in time domain includes the values that can be derived from the graphical representations of the characteristics of the signal. The graphical representation can include the density distribution, histogram representation and many such geometric methods. The geometrically expressed signals produce different useful information that can be formulated using the parameters in the Table 2

Frequency domain measures:

Linear methods also include frequency domain measures. These measures are used for calculating the power function of the each band of frequency. The range of frequency canbe adjusted from low to high and also in e intermediate position. Power of each band of frequency can differ for normal and arrhythmic signals. Hence the parameters derived from the signal can be more informative. Few of the parameters related to frequency are listed in the Table 3

Nonlinear methods:

Parameters which do not have a proper standard but are a promising tool for the assessment of characteristics in different types of signals. These features do not correspond to the change in input to the change in output. Error in the signal is determined as change in the appearance at each point of the occurrence. The deviation of these value from the mean of the signal will correspond to the parameters that are determined as the informative part in the processing of the signal. Some of the nonlinear parameters are listed in the Table 4.

The above mentioned parameters with different characteristics are the most frequently used parameters i the analysis of any form of ECG signal. There are man other parameters in literature that might also be helpful i deducing the character of the normal and arrhythmi signals. The few parameters that obtained from wavele transform of the signal are wavelet coefficients [7, 9, 41 58, 63], statistical features from the transform [62], combining wavelet transform features with S transform [44], wavelet variance estimation [3] and many others. Power spectrum analysis is also done to determine the variation required to differentiate the normal and abnormal wave. The forms of parameters from power spectrum analysis are, power spectral density [8,13,14, 27], higher order spectrums like bicoherence and bispectrum plots [13], power spectral features like Gaussian Radial Basis Function, Kernel Parameter, C penalty parameter [49] are being used in literature for better analysis of the signals.

3.2 Feature Dimension Reduction:

In obtaining the ability to make the working platform learn the features and their characteristics, machine learning is necessary. Dimensionality reduction in this point is the process by which a whole set of random variables are being reduced in number to obtain the most predominant and principal variables. Reduction is mainly done to reduce the processing time and the memory required to store all the available data. This also increases the performance and efficiency of the algorithm to which they are put in with.

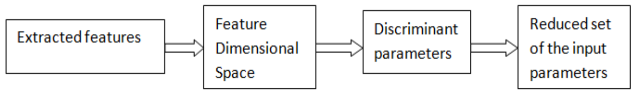

Figure 5 .Block diagram of Feature Dimension Reduction

According to the survey, few techniques in dimension reduction are used in some of the research where a large number of parameters are taken into consideration. The techniques used are described in table 5.

Table 4 .List of nonlinear features

S.No	Feature	Description
1.	Fano Factor	It is the ratio of variance of the signal to the mean of the same [3, 34].
2.	Allan Factor	Measure of error from the mean value determined for successive points [3, 34]
3.	ncare Plots SD1/SD2	Quantifies the closeness of statistically similar scales in the plot. [6, 10, 14, 16, 21,34]
4.	Detrended Fluctuation Analysis (DFA)	It was conceived as a method for detrending variability in a sequence of events. [3, 16, 21, 61]
5.	,argest Lyapunov Exponent (LLE)	It characterizes the rate of separation of closely located trajectories. [6, 11, 14, 16, 21]
6.	Spectral Entropy	[6, 14, 16, 21]
7.	Correlation Dimension	It is the measure of the dimension of the points under consideration.[5, 25]

Table 5 .List of reduction algorithms

S.No	Technique	Description
1.	Linear Discriminant Analysis (LDA)	Disintegrating a complete feature space with a set of a number of variables onto a smaller space while maintaining the necessary information [9].
2.	Generalized Discriminant Analysis (GDA)	Extends the mapping of LDA to nonlinear mappings [14].
3.	Fuzzy C-Clustering (FCM)	ıch a way that they belong to more than one cluster [33].
4.	article Swarm Optimization	parameters among the extracted parameters [49,55].

3.3 Classification Algorithms:

There are various types of arrhythmia that are life threatening. Automated classification of these malfunctions play a major role in the diagnosis and treatment of the same. This process of classification is done using different forms of algorithms. The algorithms are effective based on their efficiency and time taken for computation. Computation depends on the mathematical model and the procedure involved in analyzing the signal under consideration.

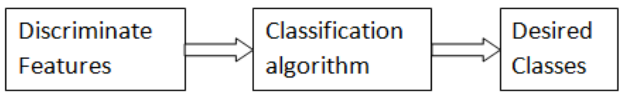

Figure 6 .Block diagram of Classification

In literature there are a numerous methods used as classification algorithms. For higher performance two or more algorithms are fused and are made to give better outcome. The table below shows the different forms of both direct and fusion form of algorithms used in various research.

Table 6 .List of classification algorithms

S.No	Classification Algorithm	Description
1.	Fuzzy equivalence relation classifier	Hierarchical classification based on the fuzzy equivalence relation of the parameters [5,21].
2.	Neural Network	Trained neurons are arranged in layers for the input parameters and produces the required output [5,6,16,22,51,53]
3.	ANFIS	Adaptive Neuro-Fuzzy interference system integrates both the functionalities of neural network and fuzzy logic [7,12, 24, 27,35,37,39]
4.	SVM Classifier	Support Vector Machine does linear or nonlinear classification by mapping the inputs to certain separate categories [9,11,25,49,55,56,62]
5.	MLP	Multilayer Perceptron is an artificial neural network model that is trained to map input sets to corresponding output sets [9,14, 44, 61]
6.	RBFNN	Radial Basis Function Neural Network is the same ANN that will use radial basis functions as activation functions for the network [17,61]
7.	GRA Classifier	Grey Relational Analysis classifies even the inputs that are uncertain and incomplete [20]
9.	C4.5	Develops a decision tree which can be used as a statistical classifier[25]
10.	Random Forest Classifier	Constitute multiple decision trees that learns ever highly irregular patterns [25,34,63]
11.	Fuzzy clustering classifier	Nonlinear algorithms wherein the inputs are clustered in an unsupervised manner [29]
12.	Fuzzy C-means Clustering – PCA – Neural Network	Integration of the three algorithms with the first stage analyzing the distribution of the parameter values, second stage features are extracted from the clusters, and third stage classifiers the input vector [33]
13.	Neuro-ANFIS	Neural network is used for determination of discriminate parameters and the output is classified using ANFIS [36]
14.	Rough Sets and Quantum Neural Network	Rough sets of the parameters are obtained and using quantum mechanics, classification is performed[41]
15.	Kernel SVM	Classes are classified by obtaining the kernel of the parameters in the feature space [42, 47]
16.	Morphological Descriptor time- frequency distribution	Spikes are classified by obtaining the kernel of the parameters in the feature space [43]
18.	Naïve Bayes Classifier	Classifies the signal on the basis that each feature obtained are independent of the other features [45]
20.	GANN Classifier	Discriminant features are obtained by genetic algorithm and these features are used as input vectors to neural network for classification [50]
21.	Cascade classifier	The output of one classifier is taken as input to another classifier
		for further classification into classes [58]
22.	K-nearest neighbor	Classes are obtained by the presence of majority number of nearest points according to the K value [54]
23.	Probabilistic Neural Network	In this classifier the distance or the difference between the input vectors to that of the training vectors are obtained and these values are summed up for each classes. A transfer function of the classes gives the unit probability of the target [61]

4. CONCLUSION:

From the above analysis made from different literature papers, ECG signal being an absolutely important electrical activity of heart, is classified using different techniques. Though the procedure followed in the analysis of the signal is same, the methods used in each step differ in all the researches. The efficiency of each technique rely on the optimization of the uncertainty occurring within the parameters obtained from the signal.

There are different types of arrhythmia signals that cause major impact in the human body. When these signals are processed statistically, they exhibit parameter values that vary in different ranges with those of normal signals. This distinct change in the parameters help the algorithm modeled for classification to define the signal classes.

Automated detection of abnormalities always is an area considered to be made efficient. Due to the point that this deals with human life science, more studies and researches are done to make the utmost possibility of an efficient system to detect diseases at the shortest time possible. These methods of detection and classification can be automated for an easy detection of diseases.

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