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ECG Signal Analysis Using Artificial Neural Network

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Abstract: ***The concept of pattern recognition refers to classification of data patterns and distinguishing them into predefined set of classes. The analysis ECG signal is an application of pattern recognition. The ECG signal generated waveform gives almost all information about activity of the heart. The ECG signal feature extraction parameters such as spectral entropy, Poincare plot and lyapunov exponent are used for study in this paper .This paper also includes artificial neural network as a classifier for identifying the abnormalities of heart disease.***

Keywords: Artificial Neural Network, Electrocardiograph (ECG), Arrhythmia, feature extraction, Classification.

1. Introduction

Electrocardiography deals with the electrical activity of the heart. Bio-signals being non-stationary signals, the reflection may occur at random in the time-scale. Therefore, for effective diagnostic, ECG signal pattern and heart rate variability may have to be observed over several hours. Thus the volume of the data being enormous, the study is tedious and time consuming. Therefore, computer-based analysis and classification of cardiac diseases can be very helpful in diagnostic [1].

The technique used in ECG pattern recognition comprises: ECG signal pre-processing, QRS detection, feature extraction and neural network for signal classification. The early detection gives the information about heart abnormalities and increase life of human. ECG is used to measure the rate and regularity of heartbeats as well as the size and position of the chambers, the presence of any damage to the heart, and the effects of drugs or devices used to regulate the heart to acquire the signal, ECG devices with varying number of electrodes (3– 12) can be used [2].

The ECG may roughly be divided into the phases of depolarization and repolarisation of the muscle fibers making up the heart. The depolarization phases correspond to the P-wave (atrial depolarization) and QRS-wave (ventricles depolarization). The repolarisation phases correspond to the T-wave and U-wave (ventricular repolarisation) [3]. Arrhythmia or dysrhythmia is a heart disorder representing itself as an irregular heartbeat due to malfunction in the electrical system cells in the heart. It causes the heart to pump blood less effectively and causing disorders in the heart conduction process [4].Early detection of heart Disease is very helpful for living a long life and increase the improvement of our technique detection of arrhythmias. Typically, standard ECG signals can be decomposed into three different groups of basic elements and shown in figure-1.

- Waves – deviations from the isoelectric line(baseline voltage) .they are named successively : P,Q,R,S,T,U;
- Segments-isoelectric lines periods between waves.
- Intervals-periods which include segments and waves.

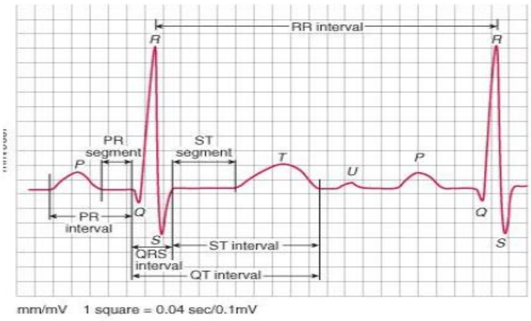

Figure 1: ECG signal

ECG signal analysis depends upon accurate and reliable detection of the QRS complex, as well as the T and P waves. The detection of QRS complex is the most important task in automated ECG signal analysis. Once the QRS have been identified, a more detailed examination of ECG signal is possible by including the heart rate and ST segment [5-6]. A number of algorithms have been introduced and discussed in the literature for detection and classification of ECG signals.

2. Literature Review

Several algorithms have been developed in the literature for detection, feature extraction and classification of ECG signals. Ramli et al. [7] used a cross correlation analysis technique to extract the important features from 12 lead ECG signal. Using the cross correlation techniques the identified values can be used to predict the type of arrhythmias. Tadejko and Rakowski [8] ,introduced an automated classifier with Kohonen self-organizing maps (SOM) and learning vector quantization (LVQ) algorithms. this paper compares the QRS complexes for classification which is based on original ECG morphology features and proposed new approach - based on preprocessed ECG morphology features. The performance of algorithms is assessed to recognize beats either as normal or arrhythimas.

Xu et al. in [9] proposed slope vector waveform (SVM) algorithm for ECG QRS complex detection and RR interval evaluation. They used Slope vector for feature extraction of ECG wave and the non-linear amplification is used to improve signal to noise ration. This paper introduces high accuracy and fast response to find the QRS detection.

Manpreet Kaur and Arora [10] proposed the K-means clustering with Squared Euclidean distance for the analysis of ECG signals. For feature extraction the parameters identified as wave shape, duration and amplitude. Using K clustering technique clustered K is summed and minimizes the sum of point to centroid distance. With the help of K clustering technique first phase give information about the points are resigned to the closet cluster around the cetroid.the second phase gives information on line value where values are self-resigned.the success rate of classification for different datasets of MIT-BIH are analyzed .

F. de Chazal et.al [23] shows the premature ventricular contraction from the normal beats and other heart diseases.For feature extraction of ECG signal the combination of the morphological based features and timing interval based features are proposed. For ECG signal classification the MLP with different no of hidden layer and algorithm according to radial basis function and probabilistic neural network is used. The simulation results show that about 97.14% for classification of ECG beats are achieved. For simulation the MIT-BIH arrhythmia database is used.

S. Mitra et.al [11] presented a rough-set theory for ECG signal analysis in this paper. A rule-based rough-set decision system is developed from time-domain features to make an inference engine for disease identification. Use of the rough set theory, helps to optimize rules for cardiac-disease identification, by which the complexity of NN can be avoided. Currently, the system is tested with three types of ECG data, namely normal, Myocardial Ischemia, and Myocardial Infarction. And the accuracy of all these types is obtained for both the trained and untrained dataset.

Castro et al. [12] proposed a wavelet transform algorithm for feature extraction from an ECG signal and identification of abnormal heartbeats. This algorithm helps to find out the best correlation with the ECG signal. .The ECG signal is first denoised by a soft or hard threshold and then each PQRST cycle is decomposed into a coefficients vector using the optimal wavelet function. The analyzed ECG signal coefficients are divided into the P-wave, QRS complex and T-wave, and summed to obtained a features vector of the signal cycles.

Nazmy et al [13] described adaptive neuro- fuzzy inference system (ANFIS) algorithm for classification of ECG wave.the feature extraction is done with the help of Independent Component Analysis (ICA) and Power spectrum and input is provided by the RR interval of ECG.In this paper the classified ECG signals are normal sinus rhythm (NSR), premature ventricular contraction (PVC), atrial premature contraction (APC), Ventricular Tachycardia (VT),Ventricular Fibrillation (VF) and Supraventricular Tachycardia (SVT).using ANFIS approach the classification accuracy is also obtained.

Alan and Nikola in [14] Introduced Chaos theory for ECG feature extraction. Various chaos methods, including correlation dimension, phase space and attractors, central tendency measure ,spatial filling index, and approximate entropy are also explained.

Yuksel and Bekir [17] have represented ANN to classify the ECG arrhythmias. Types of arrhythmias used is normal sinus rhythm, sinus bradycardia, ventricular tachycardia, sinus arrhythmia, atrial premature contraction, paced beat, right bundle branch block, left bundle branch block, atrial fibrillation, and atrial flutter have been as. These data were filtered, their R peaks found, and patterns normalised between 0-1.these patterns, used in training of ANN as separately as well as mixing all different arrhythmias.

Zhu et.al, [18] discussed the use of artificial neural networks for ECG abnormality detection.In this paper the SOM network ,BP and LVQ network were used to analyze the performance and reached an overall accuracy of these networks.

[19,20,21] also presented a comparative study of how neural network classifies the patterns from training data and recognizes if testing data holds that ECG signal patterns.

El-Khafif et al. [19] proposed ANN model to diagnose the ischemic heart disease from normal ECG signals. They used Feed forward Multilayer perceptron neural network with error back propagation learning algorithm for classification of ECG signals. In the presented work, the use of slices from higher-order statistics shows its strength in analysing and classifying nonlinear ECG dynamics

Hosseini et al. [22], have proposed a two-stage feed forward neural network for ECG signal classification. In which they have chosen two network architectures based on one stage and two stages feed forward neural networks to recognize heart abnormalities.

Manimegalai et al. [28], have implemented a discrete wavelet transform based system for detection and extraction of P wave, QRS complex, and ST segment. And found that this technique provides less computational time and better accuracy for classification, analysis and characterization of normal and abnormal patterns of ECG.

In [25,26,27] the neuro-fuzzy technique has been proposed to model the experimental data.

Golpayegani and Jafari [29] proposed a comparative assessment of performance of ANFF Adaptive Neural Fuzzy Filters (ANFF) with MLP neural networks and it is found that the training time of ANFF was much shorter than time required by MLP. Owis et al. [30] have presented the correlation dimension and largest lyapunov exponent parameters to model the chaotic nature of different classes of ECG signals. The proposed implementations were used to compute these features for a large number of independent ECG signals belonging to five different ECG signal types from the MIT-BIH Arrhythmia Database . The results are studied to detect statistically significant differences among different arrhythmia types. Finally, statistical classification techniques are used to assess the possibility of detecting and classifying arrhythmia using such parameters.

3. Artificial Neural Network

The first neural network was introducing in 1943 by the neurophysiologist Warren McCulloch and logician Walter Pits. Artificial neural networks (ANNs) are biologically inspired networks that are useful in application areas such as pattern recognition, classification etc. . The decision making process of the ANN is holistic, based on the features of input patterns, and is suitable for classification of biomedical data. Typically, multilayer feed forward neural networks can be trained as non-linear classifiers using the generalized back propagation algorithm (BPA)[15] . The BPA is a supervised learning algorithm, in which a mean square error function is defined, and the learning process aims to reduce the overall system error to a minimum. The connection weights are randomly assigned at the beginning and progressively modified to reduce the overall system error. The weight updating starts with the output layer and progresses backward. The weight update is in the direction of 'negative descent', to maximize the speed of error reduction . The step size is chosen heuristically; in the present case, a learning constant q = 0.9 was chosen. For effective training, it is desirable that the training data set be uniformly spread throughout the class domains. The available data can be used iteratively, until the error function is reduced to a minimum. The ANN used for classification is shown in Fig. 1. The input layer consisted of nodes, and, in the subsequent hidden layers, process neurons with the standard sigmoid activation function were used. The output layer had three neurons, to divide the output domain into eight classes (000 to 111).

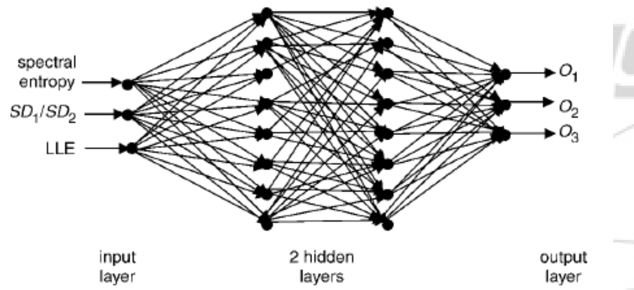

Figure 2: Four-layer feedforword neural network classifier

4. Disease Classification using ANN

For the purpose of this study, the cardiac disorders were classified into eight categories, namely (i) left bundle branch block (LBBB) (ii) normal sinus rhythm (NSR) (iii) pre-ventricular contraction (PVC) (iv) atrial fibrillation (AF) (v) ventricular fibrillation(VF) (vi) complete heart block (CHB) (vii) ischaemic/dilated cardiomyopathy (viii) sick sinus syndrome (SSS). The ANN classifier was fed by three parameters derived from the heart rate signals. They were spectral entropy, Poincare plot geometry and largest Lyapunov exponent (LLE).

4.1 Spectral Entropy

Spectral entropy quantifies the spectral complexity of the time series. A variety of spectral transformations exist. Of these, the Fourier transformation (FT) is the most commonly used technique from which the power spectral density (PSD) can be obtained. The PSD represents the distribution of power as a function of frequency. Normalisation of the PSD with respect to the total spectral power yields the probability density function (PDF). Application of Shannon's channel entropy gives an estimate of the spectral entropy of the process, where entropy is given by

$$H = \sum_{f} p_f \log\left(\frac{1}{p_f}\right) \qquad (1)$$

where p_f is the PDF value at frequency f.

Heuristically, the entropy is interpreted as a measure of uncertainty about the event at f. Thus entropy can be used as a measure of system complexity. The spectral entropy H(0<=H<=1) describes the complexity of the HRV signal. This spectral entropy H was computed for the various types of cardiac signal.

4.2 Poincare Plot Geometry

Poincare plot geometry, a technique taken from non-linear dynamics, explains the nature of R-R interval fluctuations, it is a graph of each R-R interval plotted against the next interval[30]. Poincare plot analysis is an emerging quantitative-visual technique whereby the shape of the plot is categorised into functional classes that indicate the degree of heart failure in a subject. Using plot we can obtain the summary information as well as detailed beat-to-beat information on the behaviour of the heart. The Poincare plot can be analysed quantitatively by calculating the standard deviations of the distances of the R-R(i) to the lines y = x and y = -x ÷ 2*$R\text{-}R_m$, where $R\text{-}R_m$ is the mean of all R-R(i). SD1 and SD2 are referred to as standard deviations. SD1 related to the fast beat-to-beat variability in the data, and SD2 described the longer-term variability of R-R(i) . The ratio SD_1/SD_2 can also be computed to describe the relationship between these components. Fig. 2 shows the Poincar6 plot of a normal subject.

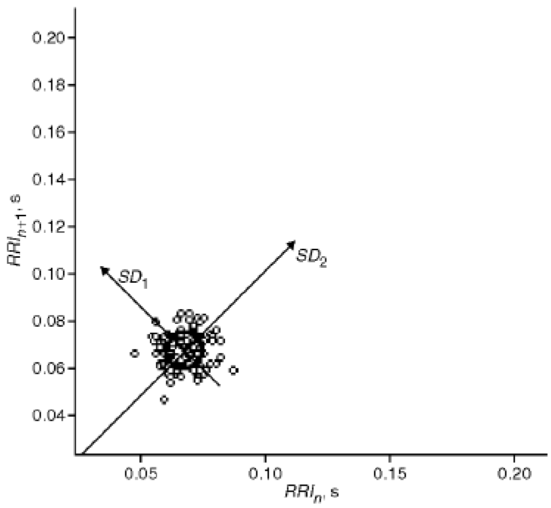

Figure 3: Poincare plot of a normal subject

4.3 Largest Lyapunov exponent

The Lyapunov exponent λ is a measure of the rate at which the trajectories separate one from another.A negative exponent implies that the orbits approach a common fixed point[5]. A zero exponent means the orbits maintain their relative positions; they are on a stable attractor. Finally, a positive exponent implies that the orbits are on a chaotic attractor. For two points in a space X_0 and $X_0 + \Delta X_0$, that are function of time and each of which will generate an orbit in that space using some equations or system of equations, then the separation between the two orbits Δx will also be a function of time. This separation is also a function of the location of the initial value and has the form $\Delta x\,(X_0,t)$. For a chaotic data set, the function $\Delta x\,(X_0,t)$ will behave unpredictably. The mean exponential rate of divergence of two initially close orbits is characterised by

$$\lambda = \lim_{n\to\alpha} \frac{1}{t} \ln\left|\frac{\Delta x\,(Xo,t)}{\Delta Xo}\right| \qquad (2)$$

The Lyapunov exponent λ is useful for distinguishing various orbits. The largest Lyapunov exponent (LLE) quantifies sensitivity of the system to initial conditions and gives a measure of predictability. The presence of a positive Lyapunov exponent indicates chaos. Even though an m dimensional system has m Lyapunov exponents, in most applications it is sufficient to compute only the LLE. So there is a need for a method which is robust with data length. This method looks for the nearest neighbour of each point in phase space and tracks their separation over a certain time evolution. The LLE is estimated using a least squares fit to an average line defined by

$$y(n) = \frac{1}{\Delta t}\Big(In\big(di(n)\big)\Big) \qquad (3)$$

where $d_i(n)$ is the distance between the i^{th} phase-space point and its nearest neighbour at the n^{th} time step.This last averaging step is the main feature that allows an accurate evaluation of the LLE, even when we have short and noisy data.

5. Further Enhancement

An ECG signal analysis, classification and the extracted attribute from the ECG signal plays very important role in diagnosing the heart disease. In addition, the further enhancement observes on utilizing different method that provides higher accuracy in feature extraction and classification.

6. Conclusion

The ECG is mainly used for diagnosis of heart disease. Various supervised and unsupervised Artificial Neural Network model have been proposed in the literature for ECG signals feature extraction and classification. The ANN classifier was fed by three parameters namely spectral entropy, Poincare plot geometry and largest Lyapunov exponent (LLE) derived from the heart rate signals are discussed.

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