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ANN FOR CLASSIFICATION OF CARDIAC ARRHYTHMIAS

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ABSTRACT

Electrocardiography deals with the electrical activity of the heart. The condition of cardiac health is given by ECG and heart rate. A study of the nonlinear dynamics of electrocardiogram (ECG) signals for arrhythmia characterization was considered. The statistical analysis of the calculated features indicate that they differ significantly between normal heart rhythm and the different arrhythmia types and hence, can be rather useful in ECG arrhythmia detection. The discrimination of ECG signals using non-linear dynamic parameters is of crucial importance in the cardiac disease therapy and chaos control for arrhythmia defibrillation in the cardiac system. The four non-linear parameters considered for cardiac arrhythmia classification of the ECG signals are Spectral entropy, Poincaré plot geometry, Largest Lyapunov exponent and Detrended fluctuation analysis which are extracted from heart rate signals. The inclusion of Artificial Neural Networks (ANNs) in the complex investigating algorithms yield very interesting recognition and classification capabilities across a broad spectrum of biomedical problem domains. ANN classifier was used for the classification and an accuracy of 90.56% was achieved.

Keywords: cardiac, arrhythmia detection, ECG, heart rate, classification, artificial neural network.

INTRODUCTION

Electrical activity of heart

The electrical signal that stimulates the heart beat starts from the Sino Atrial node (SA) is known as the heart's "natural pacemaker" and is located at the top of the right chamber or Atrium (RA). This signal branches through atria, causing them to contract and pump blood to the lower chambers, the ventricles, where the signal continues via the Atrio Ventricular node (AV). If the pacemaker is disrupted, the heart may beat at an abnormal rate, impacting the circulation of blood throughout the body.

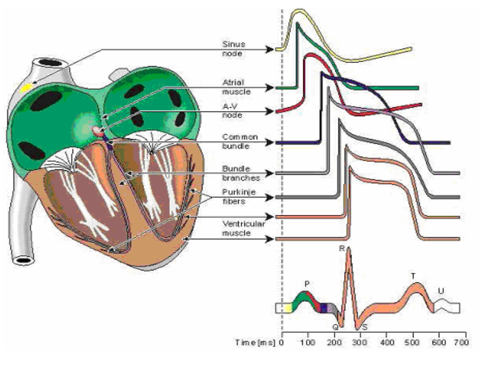

Figure-1. ECG waveform characteristics and their corresponding positions in heart.

ECG characteristics

The electrical signals described above are measured by the electrocardiogram or ECG where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. An ECG gives two major kinds of information. First, by measuring time intervals on the ECG, the duration of the electrical wave crossing the heart can be determined and consequently we can determine whether the electrical activity is normal or slow, fast or irregular. Second, by measuring the amount of electrical activity passing through the heart muscle, a pediatric cardiologist may be able to find out if parts of the heart are too large or are overworked. The frequency range of an ECG signal is [0.05-100] Hz and its dynamic range is [1-10] mV. The ECG signal is characterized by five peaks and valleys labeled by successive letters of the alphabet P, Q, R, S and T. A good performance of an ECG analyzing system depends heavily upon the accurate and reliable detection of the QRS complex, as well as the T and P waves. The P wave represents the activation of the upper chambers of the heart, the atria while the QRS wave (or complex) and T wave represent the excitation of the ventricles or the lower chambers of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified, a more detailed examination of ECG signal, including the heart rate, the ST segment, etc., can be performed. Figure-1 shows ECG waveform characteristics and their corresponding positions in heart and a typical normal ECG signal is as shown in Figure-2 [1].

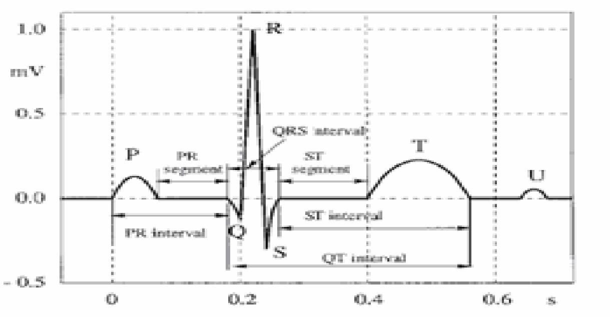

Figure-2. The ECG signal and its different components.

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REVIEW OF LITERATURE

Cuiwei Li *et al*., (1995) showed that with multi scale information in wavelets it is easy to characterize the ECG waves and the QRS complex. The difference from high P and T waves, noise, baseline drift and interference were recognized [2]. Senhadi *et al*., (1995) compared wavelet transforms for recognizing cardiac patterns. The choice of the wavelet family as well as the selection of the analyzing function into these families have been discussed to the Daubechies decompositions provided by the spline wavelet (6 levels) and the complex wavelet (10 levels) [3]. Amara Graps (1995) showed that though D6 algorithm is more complex and has a slightly higher computational overhead but it picks up detail that is missed by the Harr wavelet algorithm, which is simpler than the former. D6 of Debauchees is similar in shape to QRS complex and their energy spectrum is concentrated around low frequencies [4]. Govindan *et al.,* (1997) used a Daubechies D6 wavelet to preprocess the ECG data prior to classification using an artificial neural network [5]. Claesen and Kitney (1994) showed that the diagnostic value of the Lyapunov exponent as an indicator of decreased autonomic control of heart rate [6]. Walid El-Atabany *et al.,* (2004) applied non-linear signal processing techniques to signals like ECG to provide useful information for detection of cardiac abnormalities [7]. Sun *et al*., (2000) proposed a non-linear technique for cardiac arrhythmia detection using the ECG signal using auto regression method [8]. Silipo *et al*., (1998) has shown that the ANN's approach is shown to be capable of dealing with the ambiguous nature of the ECG signal when tested and compared with the most common traditional ECG analysis on appropriate data bases [9].

ECG feature extraction

An electrocardiogram (ECG) feature extraction system is based on the multi-resolution wavelet transform. ECG signals from Modified Lead II (MLII) are chosen for processing as the peaks of the R waves in signals from the ML II lead have the largest amplitudes among other leads The result of applying two Daubechies wavelet filters (D4 and D6) of different length on the signal is compared. The wavelet filter with scaling function more closely similar to the shape of the ECG signal achieved better detection [10]. DB wavelet family is similar in shape to QRS complex and their energy spectrums are concentrated around low frequencies the signal is approximated by omitting the signal's high frequency components. The ECG signal and the details for eight wavelet scales were used which were scaled for better illustration. The detection of R peaks is shown in Figure-3.

ECG data used

All the ECG data required for this work is used from the MIT-BIH dataset has been used [11].

Non-linear dynamics for ECG

Recent developments in chaos theory suggest that fluctuations could be nonrandom and play important role in the dynamics of the cardiovascular complex systems. Poor prognosis for cardiological patients with diminished heart rate variability (HRV) is clinically confirmed. Fluctuations in the frequency and time domain may reveal significant information on the dynamic characteristics lost with routine averaging or linear spectral methods. New computational techniques for the analysis of non-linear dynamics such as correlation dimension, recurrence plot analysis, non-stationary fluctuation analysis, detrended fluctuation analysis are useful in revealing the extent of long-range correlations in time series (x). We applied this approach to data analysis in classification work [12]. The four parameters considered for cardiac arrhythmia classification using ANN were:

1. Spectral entropy.
2. Poincaré plot geometry.
3. Largest Lyapunov exponent.
4. Detrended fluctuation analysis.

Spectral entropy

Spectral entropy quantifies the spectral complexity of the time series. Application of Shannon's channel entropy gives an estimate of the spectral entropy of the process, where entropy is given by:

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

Where pf is the PDF value at frequency f. 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 [13].

Poincare plot geometry

A physiological oscillator model of which the output mimics the shape of the R-R interval Poincare plots was used. To validate the model, simulations of various nervous conditions are compared with heart rate variability (HRV) data obtained from subjects under each prescribed condition. By exploiting the oscillator basis, we detail the way that low- and high-frequency modulation of the sinus node translates into R-R interval Poincare plot shape by way of simulations and analytic results [14]. With this, we establish that the length and width of a Poincare plot are a weighted combination of low- and high-frequency power. This provides a theoretical link between frequency-domain spectral analysis techniques and time-domain Poincare plot analysis. We ascertain the degree to which these principles apply to real R-R intervals by testing the mathematical relationships on a set of data and establish that the principles are clearly evident in actual HRV records [15 and 16].

Largest lyapunov exponent

Detecting the presence of chaos in a dynamical system is an important problem that is solved by measuring the largest Lyapunov exponent. Lyapunov exponents quantify the exponential divergence of initially close state-space trajectories and estimate the amount of chaos in a system. In this work the method proposed by Rosensetien *et al.,* (1993) which is robust with data length is used. This method looks for nearest neighbour of each point in phase space and tracks their separation over certain time evolution. Detecting the presence of chaos in a dynamical system is an important problem that is solved by measuring the LLE. For two points in a space X0 and X0 + ΔX0, 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 Δx (X0, t). For a chaotic data set, the function Δx (X0, t) will behave erratically. The mean exponential rate of divergence of two initially close orbits is characterized by:

$$\lambda = \lim_{t\to\alpha} \frac{1}{t} \ln \frac{\left|\Delta x(X_0,t)\right|}{\left|\Delta X_0\right|} \tag{2}$$

The LLE is estimated using a least squares fit to an average line defined by:

$$y(n) = \frac{1}{\Delta t}\left\{\ln\left(d_i\left(n\right)\right)\right\} \tag{3}$$

Where d_i (n) is the distance between the ith phase-space point and its nearest neighbour at the nth time step, and <,>denotes the average overall phase-space points. This last averaging step is the main feature that allows an accurate evaluation of the LLE, even when we have short and noisy data [17].

Detrended fluctuation analysis

The detrended fluctuation analysis (DFA) is used to quantify the fractal scaling properties of short interval R–R interval signals. This technique is a modification of the root-mean-square analysis of random walks applied to non stationary signals (18). The root-mean-square fluctuation of an integrated and detrended time series is measured at different observation windows and plotted against the size of the observation window on a log–log scale. The root-mean-square fluctuation of this integrated and detrended series is calculated using the equation

$$F(n) = \sqrt{1/N \sum_{k=1}^{N} [y(k) - y_n(k)]^2}. \tag{4}$$

All the four non-linear parameters are computed for the entire database.

Arrhythmia classification

Arrthymia considered for the purpose of this study 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) Ischemic dilated Cardiomyopathy

(viii) Sick sinus syndrome (SSS) [19].

For the classification of cardiac arrhythmias using ANN we have taken the analysis of spectral entropy, Poincare plot geometry, detrended fluctuation analysis and largest Lyapunov exponent as the input variables which are derived from heart rate signals. The specific values [20] for the different arrhythmias chosen are shown in Table-1.

Table-1. Range of input parameters to ANN classification model.

Class	SE	Sd1/sd2	LLE	α- slope
LBBB	1.24±0.047	0.7±0.20	0.47±0.044	0.43±0.11
NSR	1.63±0.025	0.8±0.16	0.50±0.058	0.77±0.076
PVC	1.14±0.057	1.42±0.54	0.62±0.003	0.27±0.014
AF	1.20±0.037	2.98±1.56	0.56±0.112	0.13±0.043
VF	1.06±0.003	1.13±0.47	0.42±0.036	0.34±0.022
CHB	0.86±0.054	0.64±0.02	0.078±0.114	0.54±0.034
ISCH	1.12±0.11	0.59±0.37	0.193±0.066	0.97±0.11
SSS	1.27±0.135	0.96±0.32	0.82±0.102	0.55±0.013

NEURAL NETWORK CLASSIFIER

A method is proposed to accurately classify cardiac arrhythmias through a combination of wavelets and artificial neural network (ANN) [21]. The ability of the wavelet transform to decompose signal at various resolutions allows accurate extraction/detection of features from non-stationary signals like ECG. A set of discrete wavelet transform (DWT) coefficients, which contain the

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maximum information about the arrhythmia, is selected from the wavelet decomposition [22 and 23]. These coefficients in addition to the information about RR interval are utilized to compute the non-linear parameters utilized in this work. These are fed to the back-propagation neural network which classifies the arrhythmias. As the nature of class boundaries are not clearly known, as in this present case, four-layer feed forward neural network with Log-sigmoid activation function is being used as classifier Back-propagation classifiers form non-linear discriminant functions using single- or multi-layer perceptrons with sigmoid non-linearties. They are trained with supervision, using gradient-descent training techniques, called back propagation which minimize the squared error between the actual outputs of the network and the desired outputs. Patterns are applied to input nodes that have linear transfer functions. Other nodes typically have sigmoid non-linearties. The desired output from output nodes is ‘‘low’’ (0 or < 0.1) unless that node corresponds to the current input class, in which case it is “high” (1 .0 or > 0.9). Each output node computes a non-linear discriminant function that distinguishes between one class and all other classes [21]. The BPA is a supervised learning algorithm, in which a sum square error function is defined, and the learning process aims to reduce the overall system error to min value for effective training, it is desirable that the training data set be uniformly spread through out the class domains. 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.

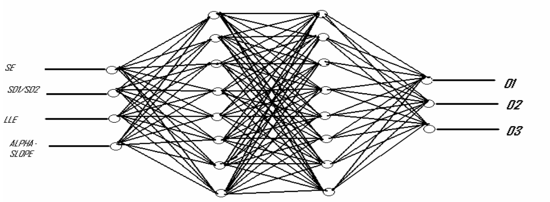

Figure-3. Four layer feed forward neural network classifier.

The output (target) vector is defined with a combination of 1 or 0s to represent each of the classes being recognized. As three neurons are chosen for the output layer combination of outputs are available ($2^3 = 8$), the output as 000 to 111. The non-linear parameters are used as inputs to ANN and the classification is done. The output of the classifier is a graphical representation. A few of them are shown in results. The classification results are tabulated in Table-2.

Table-2. Classification of cardiac arrhythmia using ANN.

Cardiac signal condition	data sets testing	correctly classified	sets mis-classified	% Accuracy
LBBB	14	13	1	92.85
-NSR	31	30	1	96.77
PVC	65	58	7	89.23
AF	20	18	2	90
VF	47	42	5	89.36
-CHB	20	18	2	90
ISCH	18	16	2	88.9
-SSS	18	16	2	88.9
Total	**233**	**211**	**22**	**90.56**

RESULTS AND CONCLUSIONS

A dynamical analysis of heart rate behaviour derived from non-linear mathematics can reveal abnormal patterns of RR interval dynamics which cannot be detected by commonly employed moment statistics of heart rate variability. The HRV signal can be used as a reliable indicator of heart diseases. ANN model is most suitable for those tasks to which there is least or limited knowledge about input variables and rules. The ANN classifier can be a diagnostic tool to aid the physician in the analysis of heart diseases. The results show that the proposed method is effective for classification of cardiac arrhythmia with an overall accuracy of 90.56% (Table-2). The results conclude that it is possible to classify the cardiac arrhythmia with the help of multilayered network driven by BPA. The advantage of the ANN classifier is its simplicity and ease of implementation.

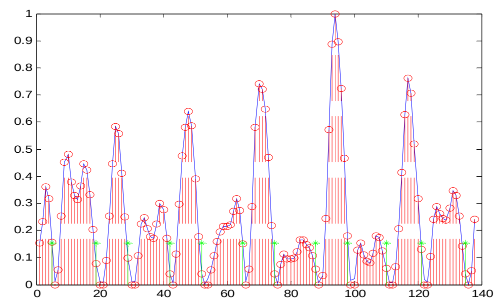

Figure-4. R peak detection.

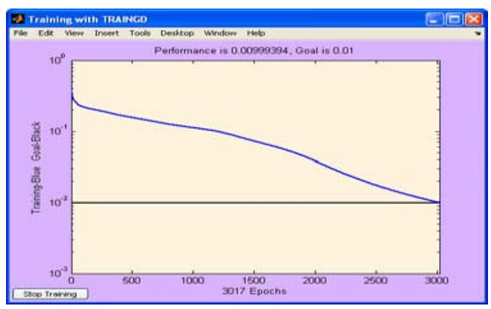

Figure-5. The training performance ANN.

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Figure-6. The output of cardiac signal-LBBB.

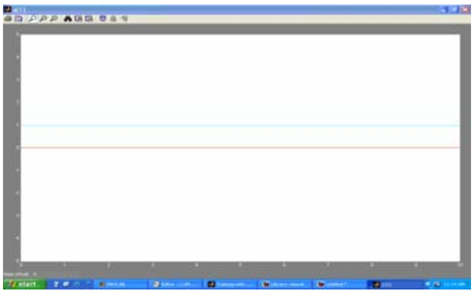

Figure-7. The output of cardiac signal- NSR.

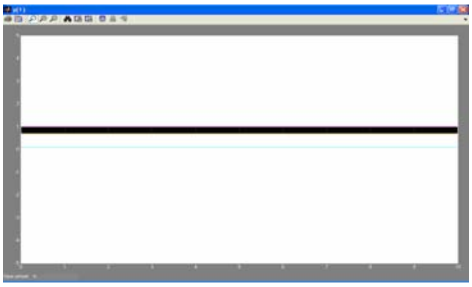

Figure-8. The colour code in the figure indicating misclassification.

REFERENCES

[1] Joseph J. Carr and John M. Brown. 2001. Introduction to Biomedical Equipment Technology. Pearson Education Inc.

[2] Cuiwei Li, Chongxum Zheng and Changfeng Tai. 1995. Detection of ECG characteristic points using wavelets transforms. IEEE Transactions on Biomedical Engineering. 42(1): 21-28.

[3] Senhadi L, Carrault G, Bellanger J.J. and Passariello G. 1995. Comparing Wavelet Transforms for Recognizing Cardiac Patterns. IEEE Engineering in Medicine and Biology Magazine. 14(2): 167-173.

[4] Amara Graps. 1995. An Introduction to Wavelet. IEEE Comp. Sc. and Eng. 2(2).

[5] Govindan A, Deng G. and Power J. 1997. Electrogram analysis during atrial fibrillation using wavelet and neural network techniques. Proc. SPIE 3169. pp. 557–62.

[6] Claesen S. and Kitney R.I. 1994. Estimation of the largest Lyapunov exponent of an RR Interval and its use as an indicator of decreased autonomic heart rate control. IEEE Computers in Cardiology. pp. 131-136.

[7] Walid El-Atabany. 2004. Nonlinear dynamical modeling of ECG signals based on phase density matrix representation.

[8] Sun Y, Chan K.L. and Krishnan S.M. 2000. Arrhythmia detection and recognition in ECG signals using nonlinear techniques. Ann. Biomed. Eng. 28, S-37.

[9] Silipo R. and Marchesi C. 1998. Artificial Neural Networks for automatic ECG Analysis. IEEE Transactions on signal processing. 46(5): 1417-1425.

[10] MIT-BIH arrhythmia database. 3rd Ed. 1997. Harvard-MIT Division of Health Science Technology, Biomedical Health Centre, Cambridge, MA, USA.

[11] Mietanowski M, Szelenberger, A. Trzebsk. 2006. Non Linear Dynamics of the cardiovascular parameters in sleep and sleep apnea. Journal of Physiology and Pharmacology. 57(11): 55-68.

[12] Rezek I. A. and Roberts S. J. 1993. Stochastic complexity measures for physiological signal analysis. IEEE Trans. Biomed. Eng. pp. 1186-1190.

[13] Woo. M.A, Stevenson W.G, Moser, D. K. Trelease.R.B. and Harper. R. H. 1992. Patterns of beat-to-beat heart rate variability in advanced heart failure. Am. Heart J. 123: 704-710.

[14] Kaman. P.W., Krum. H. and Tonkin. A. M. 1996. Poincare plot of heart rate variability allows quantitative display of parasympathetic nervous activity. Clin. Sci. 91: 201-208.

[15] Tulppo M., Makikallio T.H, Takala T.E.S. and Seppanen K.H. 1996. Quantitative beat-to beat analysis of heart rate dynamics during exercise. Am. J. Physiol. 71: H244-252.

[16] Rosensetien. M., Colins J. J. and DE Luca C. J. 1993. A practical method for calculating largest Lyapunov exponents from small data sets. Physica D. 65: 117-134.

[17] Huikuri H V, Makikallio T H, Peng C K, Goldberger A L, Hintze U and Moller M. 2000. Fractal correlation properties of R-R interval dynamics and mortality in patients with depressed left ventricular function after

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an acute myocardial infarction Circulation. 101: 47–53.

[18]Maurice Sokolow, Malcolm B.Mcllroy, Melvin D.Cheitlin. 1990. Clinical Cardiology. Prentice Hall Int., 5th Edition.

[19]Acarya R, A. Kumar , P. S. Bhat , C. M. Lim, S. S. Iyengar, N. Kannathal and S. M. Krishnan. 2004. Classification of cardiac abnormalities using heart rate signals. Med. Biol. Eng. Comput. 42: 288-293.

[20]Bortolan G, Brohet C, Fusaro S. 1996. Possibilities of using neural networks for diagnostic ECG classification. Journal of Electrocardiology. 29: 10-16.

[21]Margarita Sordo. 2002. Introduction to Neural Networks in Healthcare-A review.

[22]Gholam Hosseini, D. Luo, K. Reynolds. 2006. The comparison of different feed forward neural network architectures for ECG signal diagnosis. Medical Engineering and Physics. 28(4): 372-378.

[23]Yegnanarayana B. 2007. Artificial Neural Networks. Prentice Hall, India.