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Performance of ANN Classifier Using HRV Analysis for ECG Database

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Abstract: Arrhythmias are the abnormal heartbeats inn which ventricular arrhythmias are a fatal type of them. The timely prediction and classification of this irregularity can help in saving life or human health. In this study, Artificial Neural Network (ANN) classifier has been tested on MIT-BIH database to predict and to classify the ventricular arrhythmias using HRV analysis. HRV or heart rate variability is a low frequency signal showing variations in heart beats andcan be efficiently utilized in the analysis of ECG signals. First, the preprocessing of the available database is done by de-noising and finding the peaks, then the HRV signal is built. ANN is used as a classifier to predict and classify the HRV signals into various arrhythmias.

Key words: Artificial neural networks, electrocardiography, heart rate variability, biomedical signal processing, pattern recognition, various

INTRODUCTION

Ventricular arrhythmia remains the most common cause of sudden cardiac death in Western societies occurring in 12: 1,000 inhabitants per year. A major challenge in current cardiology that is still an unresolved problem is to predict who will die suddenly from ventricular arrhythmias. The most frequent cause of ventricular arrhythmias and sudden cardiac death in individuals over the age of 30 is coronary artery disease, while inherited cardiac disease is the most frequent cause in individuals below 30 years of age. Unfortunately in the majority of patients dying suddenly, death is the first symptom of the heart disease (Berntson *et al*., 1997).

In this research, a classifier is trained to distinguish and detect the fatal ventricular arrhythmias and the study was based on HRV analysis. HRV or Heart Rate Variability is a low frequency signal shows the variation occurring in the heart rate. That is the beat to beat variations in the ECG signal can be termed as HRV. This variation is an effect of Autonomic Nervous System (ANS) of the body. ANS can be understand by two activities of the human body, sympathetic and parasympathetic. Sympathetic activities increases the heart rate while the other decreases the heart rate. Hence, the HRV signal is fetched from the ECG signal in the initial stage. This stage is also, known as preprocessing of the ECG signals which includes de-noising and peak detection of the signal. These peak information is then utilized to have HRV signal. Then to have a better training for a classifier some features were required and hence, extracted from the generated HRV signal. These features were linear and nonlinear in nature. On the basis of these features the artificial neural network is get trained for better prediction of some death causing ventricular arrhythmias (Moody and Mark, 2001) (Fig. 1 and 2).

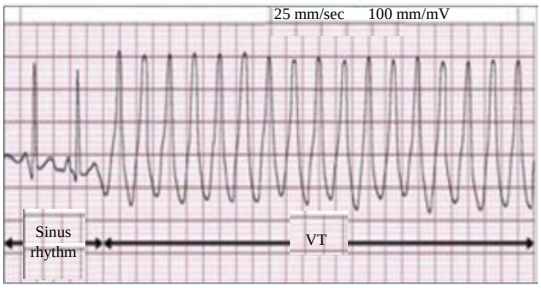

Fig. 1: Ventricular arrhythmia beats preceded by normal beats

The ECG data can be taken either from the online available databases or by volunteering process. The recorded or the downloaded data is generally very noisy so it is required to be filtered. Then HRV signal has to be extracted by detecting the R-peaks as they are the most prominent peaks found in the signal. This generated signal is then analyzed by calculating and extracting some features. On the basis of these features the data is classified into several classes required for health monitoring. Classification is hence, a very important step to be done of HRV signals for analysis and diagnosis of

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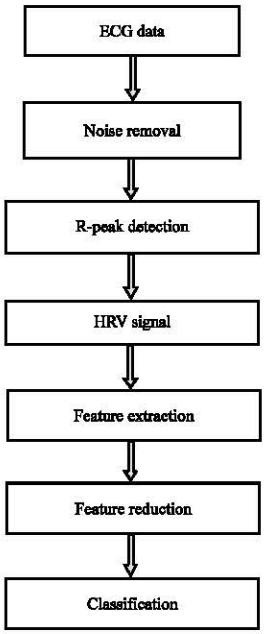

Fig. 2: Algorithm for HRV analysis

patients. The feature on the basis of which classification has to be done can be extracted from the HRV signal and can be categorized as linear and non-linear. Linear features are the time and frequency domain features and non-linear features are those features which gives the randomness in the system or the nonlinearity present in the system.

MATERIALS AND METHODS

Data acquisition and preprocessing: The first step is data acquisition. Data acquisition means to collect data which can be either done through volunteering method or data can be used from the online available various databases. MIT-BIH arrhythmia database has been used for this study. This database contains total forty eight 2-channels recordings of half an hour each. All the recordings had been digitized at 360 samples/second/channel (Camm *et al*., 1996) (Fig. 3).

The entire record have continuous ECG recordings each of 30 min duration. This data contains artifacts and noises, hence, de-noising is required at the primary stage. The preprocessing of ECG signals is done in two stages, first the de-noising of signal is done and then the peak detection in the second stage. Here in this research Pan-Tompkins Algorithm is used for preprocessing of the input ECG data (Zhang *et al*., 2006). The de-noising has following steps:

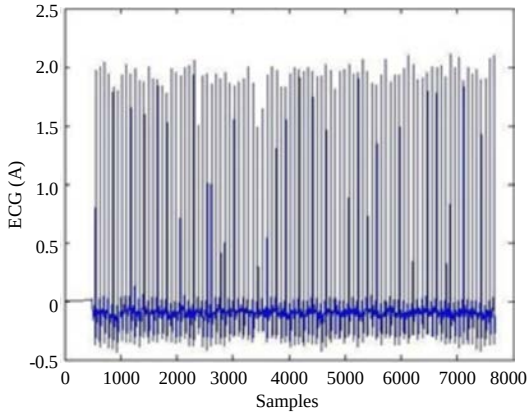

Fig. 3: A raw ECG signal

- A combination of low and high pass filter ranges between 5-15 Hz is used to tackle with the baseline wonder and muscle noise
- Then this signal is passed through a derivative filter to make the QRS complex more salient
- The derivated signal is then squared
- Now the signal is averaged with a moving window to get rid of thee noises. The length of moving window is chosen 0.150 sec
- Filtering options mainly depends on the sampling frequency

After filtering is done, peak detection is done. To determine whether any pulse corresponds QRS complex, neglecting a high sloped T-wave or any noise pulse, an adaptive thresholding operation and some decision rules are applied as stated:

Fiducial point: First the processing of signal is done to have same weighted unit samples. By doing this the QRS complex is localized at some single unit time.

Thresholding: While doing analysis of the output, two thresholding values are used ThrSig and ThrNoises, which changes according to the quality of the input signal. The first pass through y [n] uses these thresholds to classify the each non-zero sample (CurrentPeak) as either signal or noise. If Current peak>ThrSig that location is identified as a QRS complex candidate and the signal level (SigLev) is updated:

$$SigLev = 0.125CurrentPeak+0.875SigLev$$

If ThrNoise<CurrentPeak<ThrSig, then that location is identified as a noise peak and the noise level (NoiseLev) is updated:

$$NoiseLev = 0.125CurrentPeak+0.875NoiseLev$$

Based on new estimates of the signal and noise levels (SigLev and NoiseLev, respectively) at that point in the ECG, the thresholds are adjusted as follows:

$$\text{ThrSig} = \text{NoiseLev} + 0.25(\text{SigLev?NoiseLev})\text{ThrNoise} = 0.5(\text{THRSIG})$$

These adjustments lower the threshold gradually in signal segments that are deemed to be of poorer quality.

Search-back process for missing QRS complexes: If in the peak detection process, the peak detected is a false prediction or not a result of QRS complex. This will bound the false negatives. The lower threshold value for triggering this search back is 1.66 times the present peak to peak period. In this check the system assumes missing of some peak values. The time periods of beat to beat distances has some of its limitations as they cannot change drastically. Any missed beat can be matched with the highest value of the interval in which the beat has been missed. This method calculates two values of peak to peak interval, one is the mean of the last occurring peaks and the other is the mean of the most regular ones (Saxena *et al*., 2003a, b).

Elimination of multiple detections within refractory period: Human physiology draws a constraint of 200 msec as the minimum time required for a peak to occur after any other peak (Berntson *et al*., 1997). This algorithm ignores any peak detected under this constraint.

T wave discrimination: Now, if any peak is detected between the range of 200 and 360 msec from the last peak detected, the next task of this algorithm becomes to determine the genuineness of the detected peak. It may be a T-peak falsedetected as R-peak. This can be identified by analyzing the slope of the present detected peak. The slope must not less than half of the previous detected peak (Saxena *et al*., 2003a, b).

Final stage: Finally, cross verification of the R-peak which are extracted in this algorithm is done. This is done to improve the accuracy of the algorithm for the QRS detection (He *et al*., 2015) (Fig. 4).

Feature extraction: Broadly, HRV consists both linear and non-linear characteristics. The linear characteristics can be further classified in time domain and frequency domain. HRV signal reflects the changes in heart rate at every sample, hence, its time domain characteristics will depends on the deviation of the signal with time andin frequency domain the energy distribution within

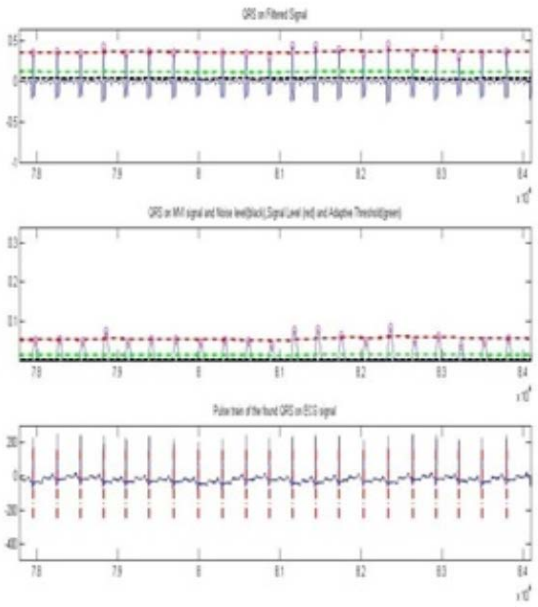

Fig. 4: QRS and R-peaks using pan tompkins algorithm

frequency band. The non-linear features may be spectral entropy, approximate entropy, correlation dimension, largest Lyapunov exponent, poincare plot, etc. (Alvarez *et al*., 2013).

Time domain features: Time and frequency domain combined are called linear feature or the analysis done based on them is called linear analysis. Time domain features can be defined as the features which are calculated with the time reference (Mehta and Lingayat, 2008). Some of the features can be extracted for time domain analysis are as follows:

- Mean-this gives the average value of the R-R intervals for each segment
- SDNN-this shows the standard deviation of the beat to beat intervals
- RMSSD-RMS of standard deviation of R-R interval can be termed as RMSSD
- NN50-NN50 gives the count of the number of samples having beat to beat interval greater than 50 msec
- pNN50-this parameter is the ratio of NN50 calculated above to the number of sample or peak to peak intervals

Frequency domain features: As the HRV signal is non-linear in nature because of certain reasons, it is unevenly distributed over samples. Therefore, the HRV signal is first made evenly sampled using the cubic spline interpolation method with sampling frequency 4 Hz. Then

the frequency domain analysis can be done. The conversion from unevenly to evenly distribution of the signal is essential for Power Spectral Density (PSD) estimation (Rao, 2015). The frequency domain features which can be extracted and analyzed are as follows:

- Total power-this parameter shows the power in the signal for all the frequencies
- Very Low Frequency-VLF for the HRV signal is a frequency band defined from 0.0033 and 0.04 Hz
- Low Frequency-LF for the HRV signal is a frequency band defined from 0.04 and 0.15 Hz
- High Frequency-HF for the HRV signal is a frequency band defined from 0.15 and 0.4 Hz
- LF/HF ratio-LF/HF is the ratio of power present in LF and HF bands of the signal

Non-linear features: Non-linear analysis is a very important analysis as it gives very useful information about the HRV signal (Kheder *et al*., 2009). There are various methods for this non-linear analysis, some of them are:

Poincare plot: Poincare plot is a graphical representation of the present sample and the next sample. That is it is the plot between successive samples of the signals. It can be calculated mathematically as SD1/SD2. SD1 and SD2 are the standard deviation of the distances of the points calculated from two lines having expression y = x and y = x+R_m where Rm is the mean of the distances of the successive heart beats respectively (Migliorini *et al*., 2013).

Correlation dimension: This feature shows the measure of complexity of the heart rate variation and describes the minimum number of dynamic variables which are used to model the systems (Sivanantham and Devi, 2014).

Largest lyuponov exponent: Largest Lyuponov Exponent (LLE) shows the dependencies of the system on the initial conditions. If chaos is present in the system the LLE will have a positive value. For calculating this exponent a value is first selected in a phase space and then the other points are calculated residing in the predefined circle of some defined radius (Pamula *et al*., 2015).

Spectral entropy: This variable shows the complexity present in the system. Greater values of spectral entropy shows greater irregularities and lesser values represents more regularity in the system (Saxena *et al*., 2003a, b) (Fig. 5).

Artificial neural network: After the advancements in artificial intelligence several methodologies were

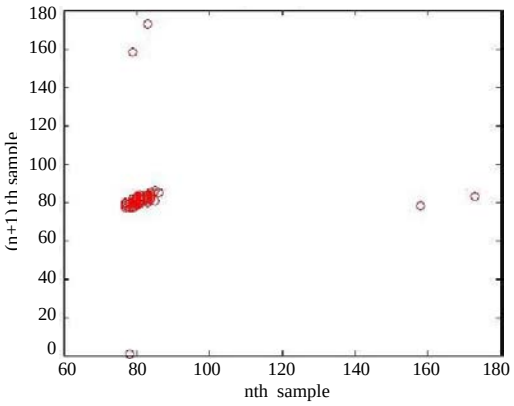

Fig. 5: A sample poincare plot

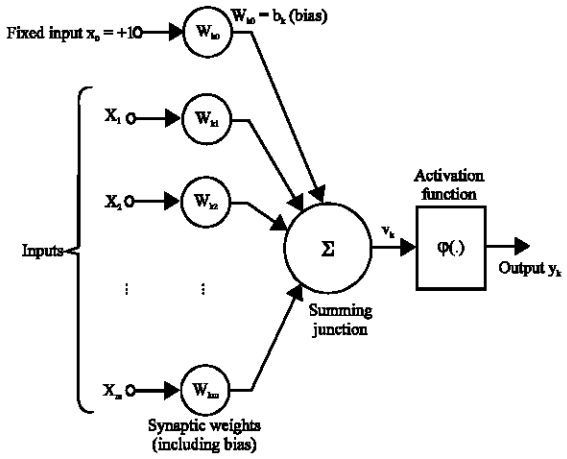

Fig. 6: A sample neural network

proposed for optimization, classification and regression purposes. Artificial neural network is one of them and finds application in various fields like biomedical signal, finance, mathematical modeling, engineering, etc (Tejera *et al*., 2011; Zhang *et al*., 2017). This is a specially designed network inspired by biological neuron which gets trained for selection after going through a large data. As the human brain classifies objects on the basis of experience of past data, neural network is also gets training first with some training data andthen the test data is applied for classification (Acharya *et al*., 2003; Sen *et al*., 2016) (Fig. 6).

The weights of neural network are regularly adjusted while training to such as to minimize the error or to increase the classification boundary. Classification boundary differentiates the available data into two or more classes. This boundary is required to be maximum so as have best separable data (Yang *et al*., 2012). Neural networks have various architectures defined

by various researchers to efficiently calculate the weights of NN architectures which can be broadly categorized as:

- Feedforward ANN
- Feedback ANN

Feedback ANNs are those with feedback path and feedforward ANNs are those with no feedback path for propagation. Most of the architectures and algorithms used for classifying data comes under feedforward ANN such as MLP, back propagation algorithm (MLP), Radial Basis Function (RBF), etc. These algorithms train the neural network by calculating and adjusting the weights (Jovic and Bogunovic, 2011; Twomey *et al*., 2014; Poddar *et al*., 2015).

RESULTS AND DISCUSSION

Linear and non-linear features have been computed for the available MIT-BIH arrhythmia database. Detrended fluctuation analysis has been done and its parameter D2 has been estimated with the input embedded dimension m have range from 1-16. Two time delay values have been chosen, first one fixed for all the samples which is equal to 1 and the other as the optimum for each RR series, i.e., the value for which the autocorrelation function drops to 1/2 times its maximum. Entropy measures have been calculated for m = 1-3 and a threshold distance r equal to 0.1 times the mean of the RR-interval series standard deviation for all recordings. Then an artificial neural network based classifier is trained using the features extracted and the corresponding output class. The training given is based on supervised learning and the algorithm used is back propagation algorithm. The output class have been developed from the corresponding information given for each data in the MIT-BIH database (Table 1).

The main objective of this study was to classify the ventricular arrhythmias from the normal and other arrhythmias affected samples. Table 1 shows the average values of nonlinear features for various c lasses.The classes chosen are "Normal" 'ventricular arrhythmia's and other two arrhythmias and atrial arrhythmia's. The table depicts clearly the variation between the ventricular arrhythmias samples and the other samples. It can also be confirmed from the table that the sample entropy can be a very effective tool or feature to classify the ventricular arrhythmias from the rest of samples. The atrial arrhythmias have highest value of entropy and the normal samples have the lowest. The same can be analyzed for other parameters also. The poincare feature SD1/SD2 has also, minimum value for the normal samples and the maximum for the atrial arrhythmias.

Table 2 and 3 gives the minimum and maximum values for the non-linear features for various classes. It has been

Table 1: Average values of non-linear features for different classes

S. No.	Sample entropy	SD1/SD2	DFA
Normal	0.0749	0.5017	1.9335
Ventricular arrhythmia	0.2099	0.9971	1.9939
AV arrhythmia	0.1304	0.5737	1.9765
Atrial arrhythmia	0.3713	0.6947	1.9847

Table 2: Minimum values of non-linear features for different classes

S. No.	Sample entropy	SD1/SD2	DFA
Normal	0.0014	0.1647	1.5217
Ventricular arrhythmia	0.0068	0.3999	1.6987
AV arrhythmia	0.0180	0.1732	1.4794
Atrial arrhythmia	0.1248	0.3977	1.4558

Table 3: Maximum values of non-linear features for different classes

S.No.	Sample entropy	SD1/SD2	DFA
Normal	0.3.73	0.9950	2.5511
Ventricular arrhythmia	0.5006	2.0094	2.4237
AV arrhythmia	0.5968	1.0500	2.3939
Atrial arrhythmia	0.8682	1.0084	2.3130

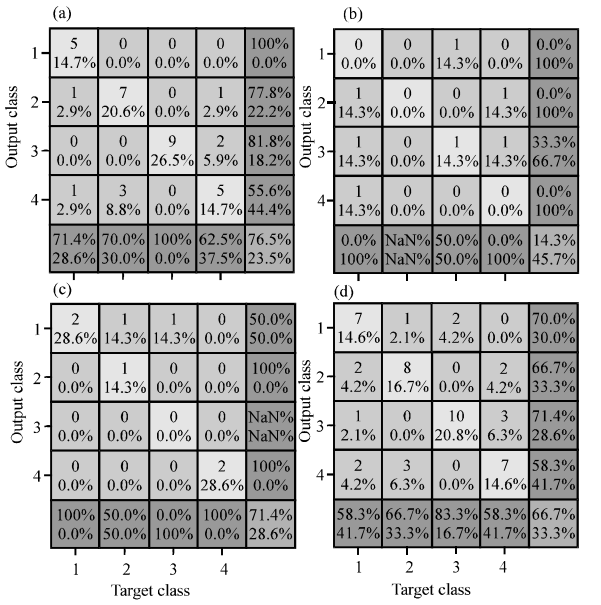

Fig. 7: ANN training for four classes, i.e., normal, ventricular arrhythmia, AV arrhythmia and atrial arrhythmia: a) Training confusion matrix; b) Validation confusion matrix; c) Test confusion matrix and d) All confusion matrix

tried to differentiate the ventricular arrhythmias then the other samples of ECG that is normal and other two arrhythmias.

The other two arrhythmias are atrial and nodal arrhythmias. AN Artificial Neural Network has been trained using these features as an input class to the ANN. And the target class has been prepared by selecting the output vectors according to the corresponding class to which the each sample belongs.

Figure 7 shows the training of ANN for four classes which are normal, ventricular arrhythmia, AV arrhythmia

and atrial arrhythmia using MIT-BIH arrhythmia database. It can be seen that the overall accuracy comes out to be 66.7% for all.

CONCLUSION

The age factor usually decreases the heart rate. Much higher heart rate variability values shows some sort of arrhythmias in the ECG signal. A fixed or constant heart rate is not a good sign but the variation should not be vary in a broad range. In this research an artificial neural network has been trained using the non-linear features of the heart rate variability and the corresponding output classes viz. normal, ventricular, atrialand nodal or junctional arrhythmias. As the neural network gets trained, it becomes capable of classifying the ventricular arrhythmias from the available other samples.

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