Enhanced Artificial Neural Network QRS Detection and PVC Diagnosis Algorithm

A. K. Mundhe
Department of Electronics and Telecommunications
Rajarshi shahu college of Engineering, buldhana
Buldhana (443310)(M.S.), India

Prof. N. A Charaniya
Department of Electronics and Telecommunications
Babasaheb Naik College of Engineering, Pusad
Pusad (445204) M.S.), India

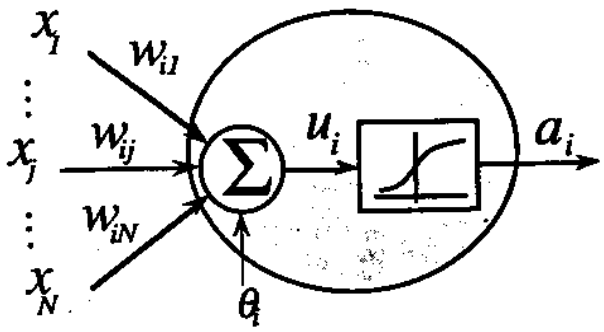
Abstract—
In this paper we proposed a automated Artificial Neural Network (ANN) based classification system for cardiac Arrhythmia and PVC (Premature Ventricular Contraction),using standard 12 lead ECG recordings. In this study, we are interested in producing high confident arrhythmia classification results for diagnostic decision support systems.
Therefore we have replaced these missing attributes by closest column value of the concern class. Multilayer percepron feedforward neural network model with static backpropagation algorithm along with Kohonen's Feature Map is used to classify arrhythmia cases into normal and abnormal classes. Networks models are trained
and tested for UCI ECG arrhythmia data set. The classification performance is evaluated using six measures; sensitivity, specificity, classification accuracy, mean squared error, receiver operating characteristics and area under curve . Our experimental results give 97.77 %. Testing classification accuracy.
Keywords- Multilayer perceptron classification, ECG arrhythmia sensitivity, specificity, accuracy, momentum learning rule.

I. *INTRODUCTION*

Cardiac arrhythmia, disorders of cardiac rhythm, may indicate the susceptibility of serious heart disease,stroke or sudden cardiac death. Early diagnosis of cardiac arrhythmia makes it possible to Choose appropriate anti-arrhythmic drugs, and is thus very important for improving arrhythmia Therapy. Various Machine learning and data mining methods have been applied to improve the accuracy for the detection of ECG arrhythmia. Method selection depends highly on the application context as given by initial task analysis, on the properties of the data on which the analysis is being performed, on previous experience with similar domains, and on user specified requirements for the results Electrocardiogram records the electronic activities of the heart, and has been widely adapted for diagnosing cardiac arrhythmia . By far, a number of signal processing pattern recognition and machine learning. Methods had been proposed. The publications of several generally available arrhythmia data sets also played an important role in stimulating research on cardiac arrhythmia diagnosis In this paper, we proposed an intelligent system, which can classify into normal and abnormal. We used multilayer perceptron feed forward neural network model with static back propagation algorithm. Presently some results achieved by carrying out the classification tasks of possible equipment integrating the most common features of the ECG analysis: arrhythmia, myocardial ischemia, chronic alterations

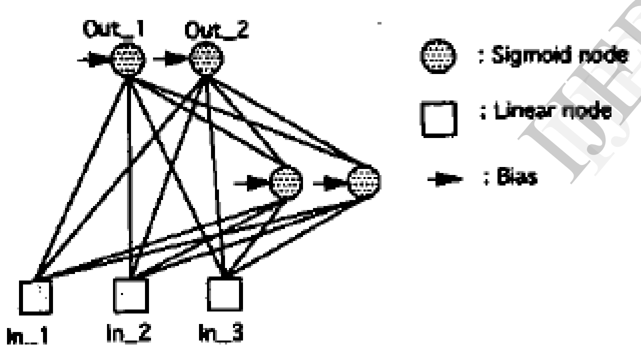
A neural network is a general mathematical computing paradigm that models the operation of biological neural systems. In ECG signal processing (detection and classification), mostly the multilayer perceptron , radial basis function networks, and learning vector quantization networks are used . An ANN structure is the interconnection of several simple nonlinear processing elements, called neurons, interconnected via weighted synapses to form a network.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 1, January - 2014



Functional Description of a Single Neuron

If neurons are grouped in layers with weighted synapses interconnecting only neurons in successive layers, the ANN structure is called a multilayer perceptron model . An MLP model is the most popular and most extensively studied ANN model. An MLP consists of an input layer and an output layer, with one or more hidden layers in between. Usually, the input layers units are linear as is the output layer. Computation occurs in the nonlinear sigmoidal hidden layers and the output layer. This is shown in Figure



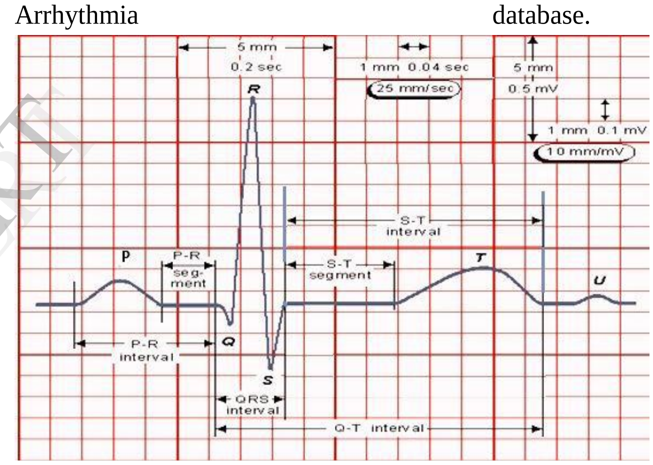
Multilayer perceptron with direct connection between input and output

The feature extraction process constitutes of either signal delineation, in which case the prominent waves and intervals in an ECG (electrocardiogram) waveform need to be determined or of some other type of feature generation scheme (such as linear or non-linear projections on some signal basis. The final step is basically feeding the generated features to a trained classifier to determine the type of the ECG beat, e.g. normal beat or resulting from premature ventricular or atrial contraction etc. Following the classification of ECG beats, we can classify the ECG rhythm (sinus rhythm, atrial /ventricular flutter/fibrillation etc) which is the most important part from a clinical perspective.

The proposed method first cleans the data set by replacing missing values by closest column values of the concern class. The use of signal analysis technique to extract the important features from the 12 lead system ECG signals. Lead II is chosen for the whole analysis due to it representative characteristics for identifying the common heart diseases.

The analysis technique chosen is the cross-correlation analysis. Cross-correlation analysis measures the similarity between the two signals and extracts the information present in the signals. Feature sets were based on Heartbeat intervals, RR intervals and Spectral entropy of the ECG signal. The ability of properly trained artificial neural networks to correctly classify and recognize patterns made them particularly suitable for use in an expert system that aids in the interpretation of ECG signals.

The ECG data is taken from standard MIT-BIH Arrhythmia database.



Normal ECG Signal and its various components

DURATION OF WAVES AND INTERVALS

Parameter	Duration (Sec)
Intervals	
P-R interval	0.12-0.20
Q-T interval	0.30-0.40
Waves	
P wave duration	0.08-0.10
QRS duration	0.06-0.10

In the normal rhythm, the PR interval should not exceed 0.20 second. The QRS duration should not exceed 0.10 second. The P wave duration should not exceed 0.10 second. The T wave should be at least 0.20 second wide. A heartbeat rate between 60 and 100 is considered "normal," so the R-R interval should be between 0.6 and 1 second.

II. *ARRHYTHMIA*

Normally, the SA Node generates the initial electrical impulse and begins the cascade of events that result in a heart-beat. For a normal healthy person the ECG comes off as a nearly periodic signal with depolarization followed by repolarization at equal intervals. However, sometimes this rhythm becomes irregular. **Cardiac arrhythmia** (also **dysrhythmia**) is a term for any of a large and heterogeneous group of conditions in which there is abnormal electrical activity in the heart. The heart beat may be too fast or too slow, and may be regular or irregular.

Arrthymia comes in varieties. It may be described as a flutter in chest or sometimes “racing heart”. The diagnosis of Arrthymia requires Electrocardiogram. By studying ECG, Doctors can diagnose the disease and prescribe the required medications

We have selected the MIT-BIH database to base our work on because it is available online where the ECG files are easily accessible and because many important works in the literature have based their work on this database and have reported their results and findings in published and widely acknowledged papers.

III. *METHODS*

A. Description of Data Set

The Cardiac Arrhythmia Database from the UCI Machine Learning Repository is used. This data set contains 452 instances of samples from 16 classes. The first class is “Normal”, and the other 15 classes are 15 kinds of arrhythmia. These 15 classes are merged into a single class called Abnormal class a representative 15 arrhythmia classes. For each sample, there are 279 attributes, where the first four, age, sex, height, and weight, are the general description of the participant, and the other 276 attributes are extracted from the standard 12 lead ECG recordings. The entire database is first preprocessed to replace missing attributes. We have used closest column value of the concern class. And later all the records are randomized.

B. Data Set Groups

The original data set grouped into different data sets and each group is partitioned into two subsets viz. training set and testing set.

C. Selection of Neural Network Model

The Multilayer Perceptron (MLP) is one of the most widely implemented neural network topologies. The article by Lippman is probably one of the best references for the computational capabilities of MLPs. Generally speaking, for static pattern classification, the MLP with two hidden layers is a universal pattern classifier. The discriminant functions can take any shape, as required by the input data clusters. Moreover, when the weights are properly normalized and the output classes are normalized to 0/1, the MLP achieves the performance of the maximum a posteriori receiver, which is optimal from a classification point of view

IV. *MIT/BIH ECG DATABASE*

The source of ECGs included in the MIT-BIH Arrhythmia database is a set of over 4000 long-term Holter recordings. Approximately 60% of these recordings were obtained from in-patients. The database contains records (numbered from 100 to 119 inclusive with some numbers missing) chosen at random from this set, and 25 records (numbered from 200 to 234 inclusive, again with some numbers missing) selected from the same set to include a variety of rare but clinically important phenomena that would not be well-represented by a small sample of Holter recordings. Each of the 48 records is slightly over 30 minutes long.

The first group of patients is intended to serve as a representative sample of the variety of waveforms and artifacts that an arrhythmia detector might encounter in routine clinical use. A table of random numbers was used to select tapes, and then to select half hour segments of them. Human experts excluded segments selected in this way only if neither of the two ECG signals was of adequate quality for analysis.Records in the second group were chosen to include complex ventricular, junctional, and supraventricular arrhythmia and conduction abnormalities. Several of these records were selected because the rhythm, QRS morphology variation, or signal quality might be expected to present significant difficulty to arrhythmia detector; these records have gained considerable notoriety among database users.

V. *ECG FEATURE EXTRACTION*

The important stage for ECG signal analysis is to extract efficient features from the signals. The features, which represent the classification information contained in the signals, are used as inputs to the classifier.

The problem faced in feature extraction is to determine what features are to be used. If there are too many features are extracted and used, the training process of the neural network will be more complex. On the other hand, if too few features are selected the classification information may be insufficient for achieving the acceptable Moreover, training of the network will be also difficult and testing results will be poor. In this research, a total of 8 features from QRS complex, QT interval and ST segment plus 4 ECG statistical features will be used.

QRS complex features

R-R, P-R, Q-T intervals and R amplitude from ECG waveforms. The FD1 algorithm proposed for QRS complex detection was applied to the ECG signal to detect the R-wave. The Q-wave and S-wave were also determined by finding a change in the slope of the ECG signal before and after the R wave. The area under the QRS complex was obtained by assuming a triangular shape for this area and the QRS duration was calculated using the following equation

QRS duration = 2x(Area under the QRS complex) / (R-wave amplitude)

The **QRS duration** is one of the main characteristics of this complex and can be used in analysis and classification of the ECG signal.

The QRS area is defined as the area located above the isoelectric line (ISO) and between the Q and S points, this area is calculated approximately as shown in the following equation:

The **PR interval** represents the time lag from the start of atrial depolarisation to the start of ventricular depolarisation and allows atrial systole to occur. The **R-R interval (RR_int)** is the distance between two subsequent QRS complexes and represents the heart beat rate (HBR).

The **R wave amplitude** is the amplitude of R wave, which is the highest distance of the height of R wave. The **R-T interval** is the intervals between the peaks of QRS complex and the consecutive peaks of T waves. The **Q-T interval** is the longest distance between Q wave and T wave. Once the QRS onset and T wave offset have been detected, the QT interval is defined as the time interval between two points: After detecting the QRS complex and the position of the R-wave, the level and slope of the ST segment were calculated. To extract accurate features from the ST segment, precise detection of the T wave is required. QRS detection techniques have been applied to the detection of the T wave with acceptable performance. The signal interval after the QRS complex is tested for a maximum slope. During this process if the maximal slope is less than half of that measured for the QR segment of the QRS waveform, it can be considered as a T wave; otherwise, it is the next QRS complex.

For a number of years, researchers worldwide have been investigating methods for real-time ECG rhythm analysis and for that sake standard databases and especially the MIT-BIH Arrhythmia Database have been an enormous help for the development and evaluation of ECG classification and detection algorithms.

VI.RESULT

ECG signal is present in .dat file,to read .dat file in to matlab it is required to convert .dat file to .m file. For the conversion various software packages are given on physionet website. By using the tools of PhysioToolkit we can convert .dat file to .mat file. This .m files are imported in to matlab and are used for the feature extraction of ECG signal.

VII.*CONCLUSION*

The great variety of QRS detection and PVC diagnostic algorithms reflect the need for a reliable method for QRS detection and PVC diagnosis in cardiac signal processing. The currently achievable detection rates reflect only the overall performance of the detectors. These numbers hide the problems that are still present in case of noisy or abnormal ECG signals. A satisfying solution to these problems is still not found. In our work, we have chosen to design and implement two techniques by which QRS detection and PVC diagnosis are achieved

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