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ROBUST SYSTEM FOR PATIENT SPECIFIC CLASSIFICATION OF ECG SIGNAL USING PCA AND NEURAL NETWORK

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Abstract: **- In this paper we present the patient specific system proposed for accurate and robust detection of ECG heartbeat pattern. In recent years many works have been proposed for ECG data classification. Detection of any disorder in heart rhythm or any change in morphological pattern which an indication of arrhythmia so finding that change for the treatment of heart patients at the early stage play an vital role . we required an effective diagnostic system as human eyes are poorly suited to detect the morphological variation of ECG signal also it is difficult for doctors to analyze long ECG records in the short period of time .In this proposed system feature extraction for the morphological feature, which are projected onto a lower dimensional feature space using Principal Component Analysis (PCA) and temporal feature from ECG data. Artificial neural network ANNs is used for pattern recognition. ANN is powerful tools for pattern recognition, as it having potential to learning complex and nonlinear surfaces. The ECG pattern classification performance strongly depends on the characterization power of the features extracted from the ECG data and the design of the classifier. Nonstationary ECG signal is effectively analyzed by the TI-DWT due to its time–frequency localization properties. PCA is well-known statistical method that has been used for data compression, data analysis, redundancy and dimensionality reduction, and feature extraction. PCA is the optimal linear transformation in which we finds a projection of the input pattern vectors onto a lower dimensional feature space that retains the maximum amount of energy among all possible linear transformations of the pattern space .The proposed classification system can adapt significant interpatient variation in ECG patterns by training the network structure, and thus we achieves higher accuracy over larger datasets.**

Index Terms - **ECG, PCA, ANN, TI-DWT.**

I. INTRODUCTION.

ECG is presented in the form of graph which is of voltage versus time, measured the electrical activity of the heart. ECG is measured using electrodes placed on the skin near around heart. These electrodes detect the small electrical changes that are a consequence of cardiac muscle depolarization followed by repolarization during each cardiac cycle. There are three main components to an ECG wave which is P wave, QRS complex and T wave. The P wave represents the depolarization of the atria, the QRS complex represents the depolarization of the ventricles and the T wave represents the repolarization of the ventricles. Diagram of ECG signal shown in fig (a)
The recorded ECG waveform shows the time evolution of the heart's electrical activity, which is made of different electrical depolarization–repolarization. System will be developed in modules, these modules are combined and training will be given to the system for patient specific classification of ECG data. For training and performance evaluation of the proposed patient specific ECG classifier .We used MIT/BIH database which having both timing information and beat class information that verified by independent experts .Change in the morphological pattern of heart may be small or disorder of heart rate is an indication of an arrhythmia which could be detected by analysis of the recorded ECG waveform. Classification of ECG beat is a challenging problem as the morphological and temporal characteristics of ECG signals show significant variations for different patients and under different temporal and physical conditions.

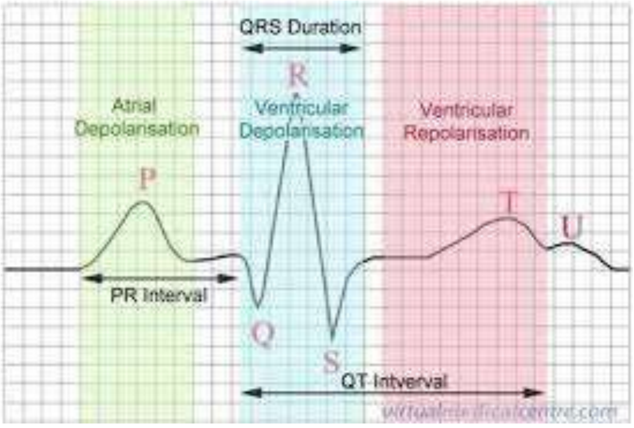

fig (a):diagram of ecg signal

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For automatic detection and classification of ECG heartbeat patterns many algorithms have been presented but ECG classifier systems based on past approaches have not performed well in practice because of their important common drawback of having an inconsistent performance when classifying a new patient's ECG waveform. This makes system unreliable to be widely used clinically and causes severe degradation in their accuracy and efficiency for larger databases.

ECG classification pattern strongly depends on the characterization power of the features extracted from the ECG data and the design of the classifier. To get separation of the relevant ECG waveform morphology descriptors from the noise, interference, baseline drift, and amplitude variation of the original signal, ECG signal can be used to decompose an according to scale by using wavelet transform. The dimension of the input morphological feature vector is reduced by projecting it onto a lower dimensional feature space using Principal Component Analysis (PCA) in order to significantly reduce redundancies in such a high-dimensional data space. To improve accuracy and robustness of system, the lower dimensional morphological feature vector is then combined with two critical temporal features related to inter beat time interval.

Pattern recognition is done by using ANN as they have the potential to learning complex, nonlinear surfaces among different classes, and such ability can therefore be the key for ECG beat recognition and classification.

II. METHODOLOGY

In the system modules will be developed for patient specific classification of ECG data. These modules are combined and training will be given to the system in which ECG data collection from MIT-BIH arrhythmia which is given to the data detection module then features will be extracted from this data, this extracted feature is given to the Principal Component analysis (PCA) for dimensionality reduction and finally it given to Artificial Neural Network (ANN) for patient classification. Proposed ECG classification system is given below in fig (b)

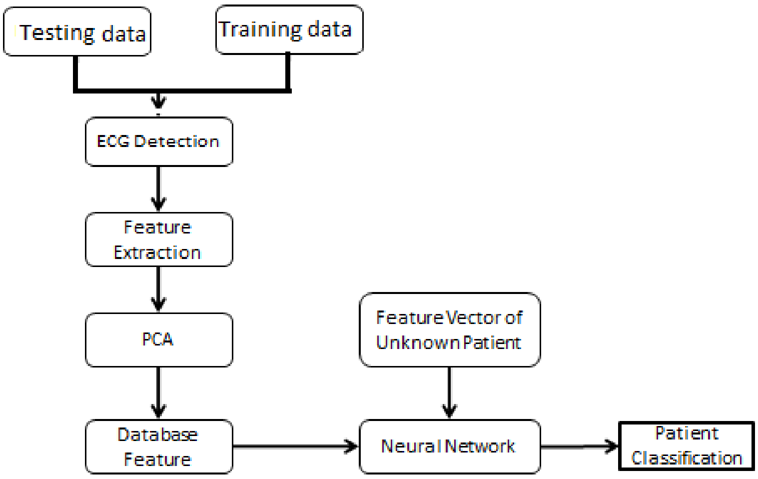

fig (b) : proposed ECG classification system

2.1 ECG Data

Here MIT/BIH arrhythmia database is used for training and performance evaluation of the proposed patient specific ECG classifier. The MIT/BIH arrhythmia database contains Interpretation for both timing information and beat class information verified by independent experts.The real time ECG signal shown in fig (c).

Here we are using different ECG signal(normal and diseased patient) as testing as well as traning database.The database contains different records of ECG signal including Hanipas,Breithman and Normal patient, fig(c) indicates record of real time ecg signal of hanipas patient and fig(d) indicates real time Hanipas ECG signal.

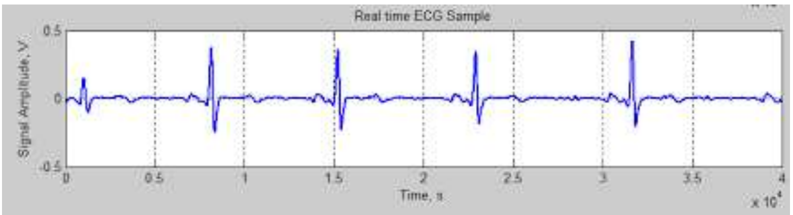

fig (c): real time ECG signal

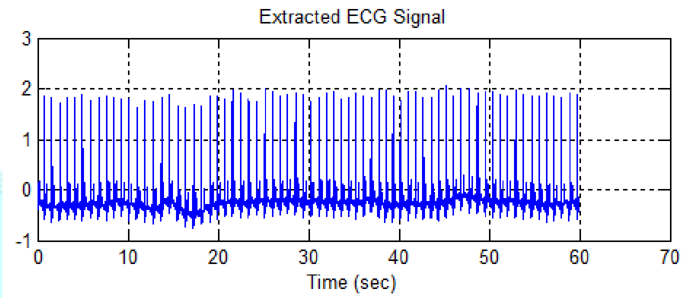

fig (d): real time Hanipas ECG signal

2.2 ECG Detection module

Eigenvector methods were applied to assign ECG beats. The ECG is detected using Eigenvector method. It play important role for estimating frequencies and powers of signals from noise corrupted signal. The Eigen vector associated with the minimum Eigen value of the estimated autocorrelation matrix is used to calculate the PSD.

These methods are based on an Eigen decomposition of the correlation matrix of the noise-corrupted signal. Even when the SNR is low, the eigenvector methods produce frequency spectra of high resolution. To gain some noise immunity, it is reasonable to retain only the principal eigenvector components in the estimation of the autocorrelation matrix, signals that can be assumed to be composed of several specific sinusoids buried in noise and for this methods are best suited

2.3 Feature Extraction module

The morphological and temporal feature will be extracted from ECG data after ECG detection using above method Wavelet transform is used to extract morphological information from the detected ECG signal. For effectively extraction of the morphological information from ECG data we can also use translation- invariant dyadic wavelet transform (TIDWT) . In TI-DWT only the scale parameter is sampled along the dyadic sequence $(2^j)_{j\epsilon z}$ and the wavelet transform is calculated for each point in time. TI-DWTs have been successfully applied to pattern recognition.QRS on filtered signal are shown in fig(e)

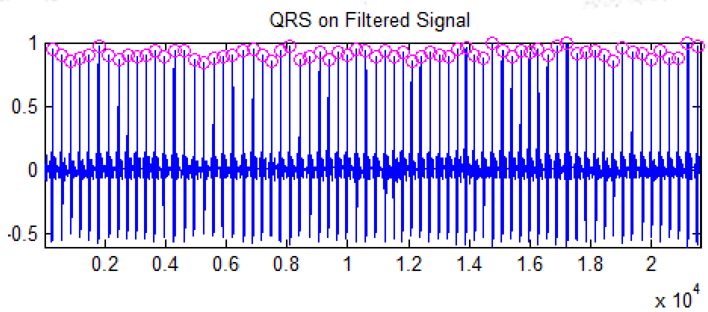

fig (e):QRS On filtered signal

2.4 Dimension reduction using PCA module

To reduce dimensionality (and redundancy) of input feature vectors are reduced by using PCA so the wavelet-based morphological features in the training set are post processed using PCA.

PCA is the optimal linear transformation, which finds a projection of the input pattern vectors onto a lower dimensional feature space that retains the maximum amount of energy among all possible linear transformations of the pattern space

Let F be a feature matrix of size K ×N, whose rows are wavelet features of size 1×N, each belonging to one of K heart beats in the training data. First, the covariance matrix C_F of this feature matrix is computed as shown in equation (1)

$$C_F = E\{(F - m)(F - m)^t\} \quad (1)$$

where m is the mean pattern vector. From the eigen decomposition of C_F ,which is a K ×K symmetric and positive-definite matrix, the principal components taken as the eigenvectors corresponding to the largest eigenvalues are selected, and the morphological feature vectors are then projected onto these principal components ,thus PCA reduced the dimensionality.

2.5 Feature Database

The feature database consisting morphological and temporal features of healthy and diseased persons can be created for training of Neural Network. In our system we having feature database of normal and diseased person

2.6 ECG data classification module

ECG beat recognition and classification will be done byANN as it having ability to learn complex, nonlinear surfaces among different classes . ANNs are used for the classification of ECG data from each individual patient in the database. ANN compares features of test case patient with the features stored in database to classify patient as normal or diseased heart patient.

III. EMPIRICAL ANALYSIS

Initially wavelet transform is used to extract morphological feature of ECG data to improve accuracy and robustness of the proposed classifier. The time-domain ECG signatures were first normalized by subtracting the mean voltage before transforming into time-scale domain using the DWT. However, due to the rate-change operators in the filter bank, the discrete WT is not time-invariant . TI-DWT, only the scale parameter is sampled along the dyadic sequence $(2^j)_{j\varepsilon z}$ and the wavelet transform is calculated for each point in time

IV. EXPERIMENTAL RESULTS

4.1 Optimality of network

We shall first demonstrate the optimality of the networks(with respect to the training MSE),which are automatically evolved by the MD PSO method according to the training set of an individual patient record in the benchmark database.

MD PSO naturally favors a low-dimension solution when it exhibits a competitive performance compared to a higher dimension counter part such a natural tendency eventually yields the evolution process to compact network configurations in the architecture space rather than the complex ones, as long as optimality prevails.

We are taking three types of ECG signal, including normal ECG and ECG signal of diseases like Hanipas and Breithman. Here all ECG signal are going to different process such as detection of ECG signal, feature extraction using TI- DWT, dimensionality reduction using PCA so we get feature database and finally data classification process by using Artificial Neural Ntw.

4.2 Classification performance

We performed classification experiments on 30 records of the MIT/BIH arrhythmia database ,in which 15 records used as training database and 15 records used as testing database according to procedure we get 80% to 90% accuracy. There are different steps done on ECG signal by using different modules to get our desired output of our system. That steps are given below also which are shows for normal and diseased heart patient ,that steps are as below

4.2.1 Step1: Extraction of ECG signal

In step first data base signal and extracted ECG signal as database signal contains contains noise, baseline drift and amplitude variation which can be removed by using TI-DWT

4.2.2 Step2: Detection of QRS on ECG signal

Step second indicates detection of QRS on ECG signal and pulse train of the QRS on the ECG signal

4.2.3 Step3:Extraction of ECG signal using QRS information

In this step extracted ECG signal using QRS information

Now all this steps can be represented as shown in figures below for ECG data

4.2.2.1 Stepwise procedure for detection of Breithman ECG signal

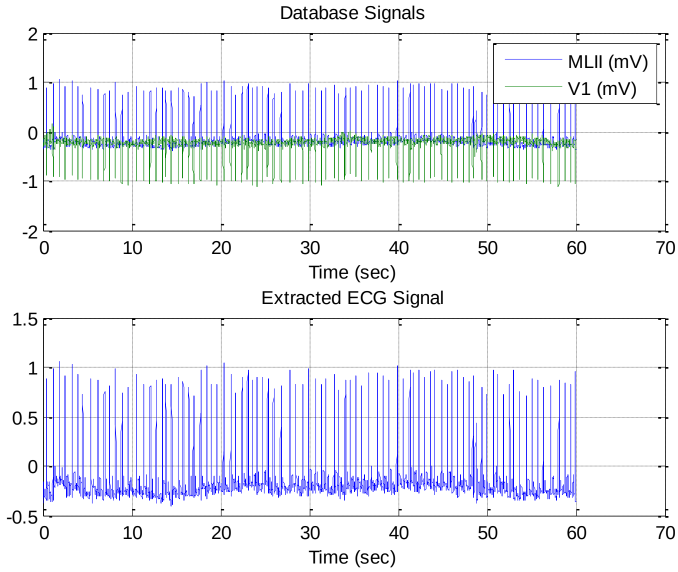

Fig (f):Extraction of ECG signal

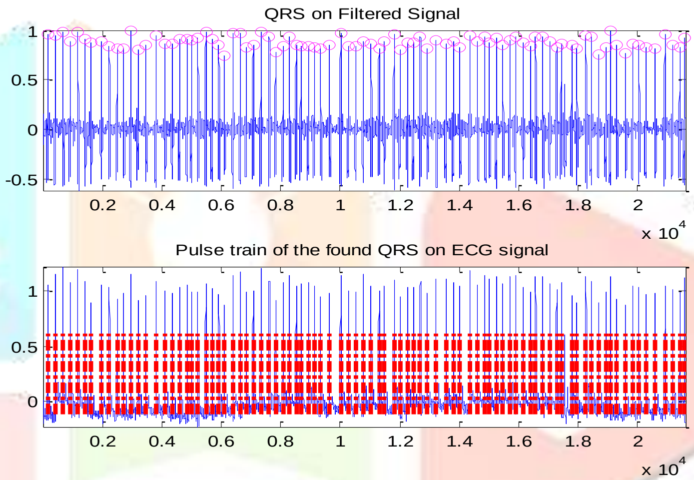

Fig (g): Detection of QRS on ECG signal

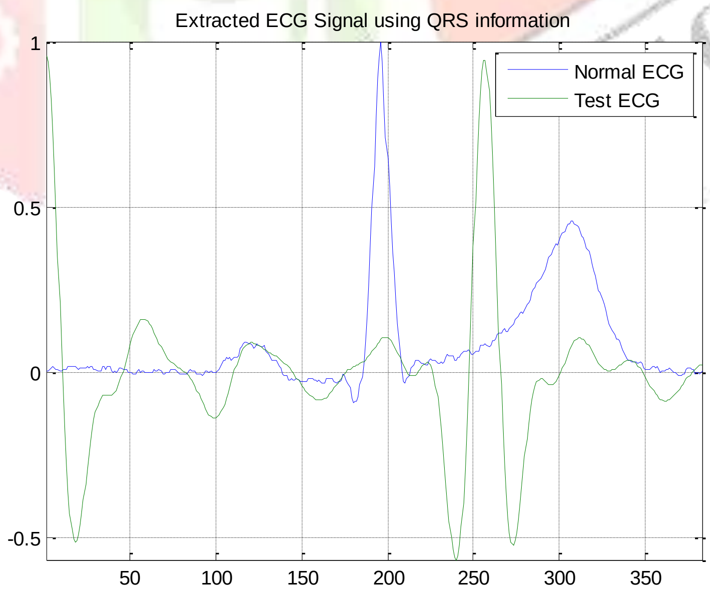

Fig (h): Extraction of ECG signal using QRS information

4.2.1 Stepwise procedure for detection of Hanipas ECG signal

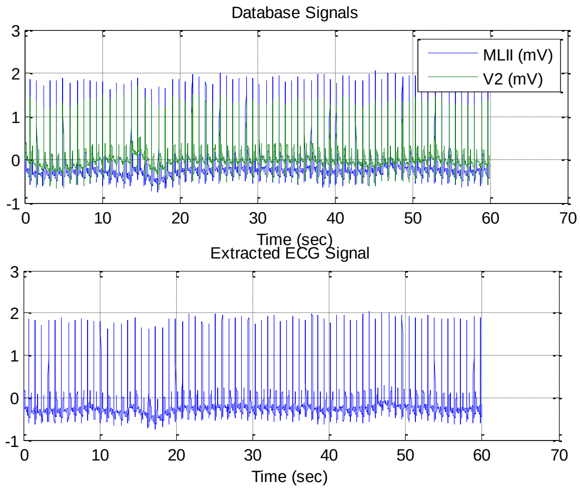

Fig (i):Extraction of ECG signal

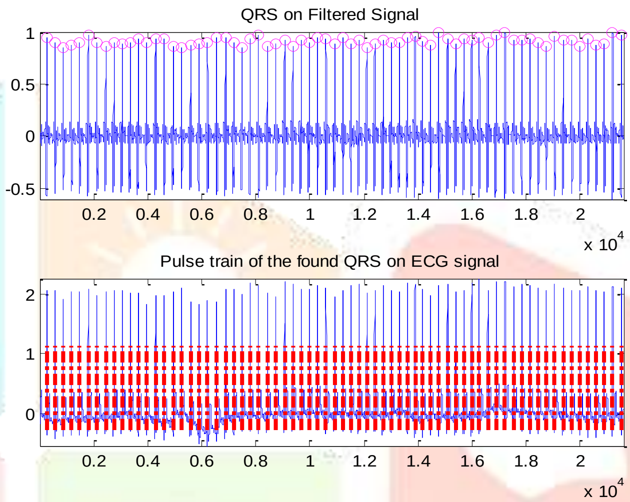

Fig (j): Detection of QRS on ECG signal

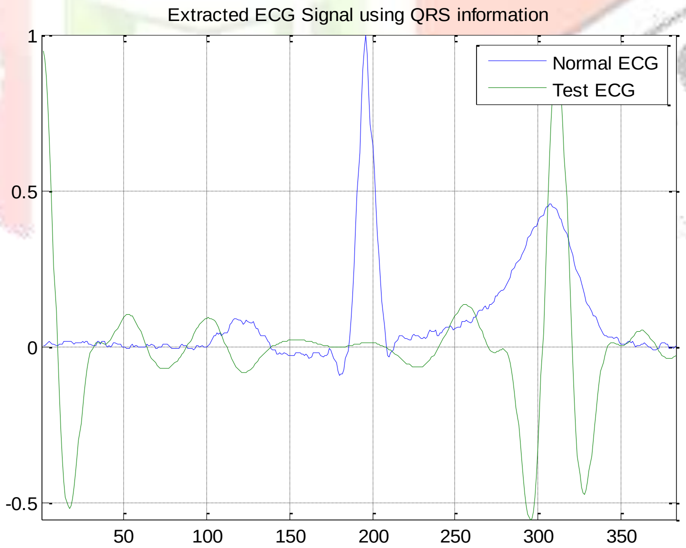

Fig (k): Extraction of ECG signal using QRS information

V. CONCLUSION

Detection of ECG arrhythmias is necessary for taking quick action for the treatment of heart patients and also for diagnosing the heart disease at the early stage. Lot of works have been proposed for ECG data classification It is very difficult for doctors to analyze long ECG records in the short period of time and also human eyes are poorly suited to detect the morphological identification of ECG signal, hence applying the need for an effective diagnostic system. The proposed method is based on only well-known standard technique such as DWT and PCA, while using the most typical ANN structure, the MLPs. Experimental results approves that its own performance is not affected significantly by variations of the few parameters used. Therefore, the resulting classifier successfully achieves the main design objectives, i.e., maintaining a robust and generic architecture with superior classification performance. So this system is useful for physician to take decision for heart condition of a patient in life threatening condition, so it is very useful to medical field.

VI. ACKNOWLEDGEMENT

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