ECG SIGNAL USING DCT-ALGORITHM AND OPTIMIZED RBFNN CLASSIFIER

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Abstract : Signal processing techniques are an obvious choice for real-time analysis of electrocardiography (ECG) signals. However, classical signal processing techniques are unable to deal with the non stationary nature of the ECG signal. In this context, this project presents a new approach, i.e., discrete orthogonal stock well transform using discrete cosine transform for efficient representation of the ECG signal in time–frequency space. These time–frequency features are further reduced in lower dimensional space using principal component analysis, representing the morphological characteristics of the ECG signal. In addition, the dynamic features (i.e., RR-interval information) are computed and concatenated to the morphological features to constitute the final feature set, which is utilized to classify the ECG signals using RBFNN based support vector machine (SVM). In order to improve the classification performance, optimization technique is employed for gradually tuning the learning parameters of the SVM classifier. In this project, ECG data exhibiting 16 classes of the most frequently occurring arrhythmic events are taken from the benchmark MIT-BIH arrhythmia database for the validation of the proposed methodology. This project is developed using Matlab simulation.

I. INTRODUCTION

Electrocardiogram (ECG) is a diagnosis tool that reported the electrical activity of heart recorded by skin electrode. The morphology and heart rate reflects the cardiac health of human heart beat [1]. It is a noninvasive technique that means this signal is measured on the surface of human body, which is used in identification of the heart diseases [2]. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of cardiac arrhythmia, which could be detected by analysis of the recorded ECG waveform. The amplitude and duration of the P-QRS-T wave contains useful information about the nature of disease afflicting the heart. The electrical wave is due to depolarization and re polarization of Na^+ and k^-ions in the blood [2].The ECG signal provides the following information of a human heart [3]: Heart position and its relative chamber size, impulse origin and propagation, heart rhythm and conduction disturbances extent and location of myocardial ischemia changes in electrolyte concentrations drug effects on the heart. ECG does not afford data on cardiac contraction or pumping function.

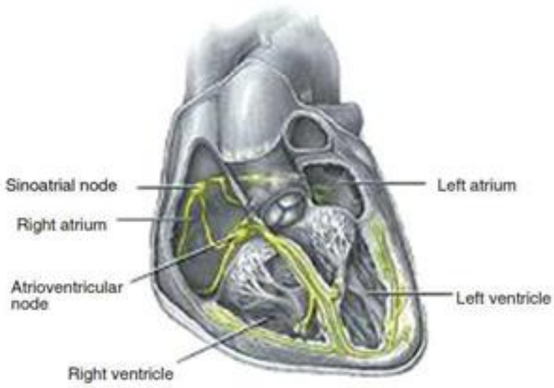

Fig. 1 The Heart conduction system.

In heart Sino-atrial (S-A) node spontaneously generates regular electrical impulses, which then spread through the conduction system of the heart and initiate contraction of the myocardium. Propagation of an electrical impulse through excitable tissue is achieved through a process called depolarization. Depolarization of the heart muscles collectively generates a strong ionic current [1]. This current flows through the resistive body tissue generating a voltage drop. The magnitude of the voltage drop is sufficiently large to be detected by electrodes attached to the skin. ECGs are thus recordings of voltage drops across the skin caused by ionic current flow generated from myocardial depolarisations[5]. Atrial depolarisation results in the spreading of the electrical impulse through the atrial myocardium and appears as the P-wave. Similarly, ventricular depolarisation results in the spreading of the electrical impulse throughout the ventricular myocardium.

II. LITERATURE SURVEY

TITLE: Heartbeat Classification Using Morphological and Dynamic Features of ECG Signals

AUTHOR: B.V.K.VijayaKuma, et al

In this paper present heart-beat classification is discussed based on a combination of morphological and dynamic features. Wavelet transform and independent component analysis (ICA) are applied separately to each heartbeat to extract morphological features. This used to derive detailed description of the morphological and dynamic functioning of the various internal organs of the body. Morphological is not testable and this is too much variation with in species.

TITLE: A Patient-Adapting Heartbeat Classifier Using ECG Morphology and Heartbeat Interval Features

AUTHOR: Philip de Chazal, et al

In this paper present Patient-Adapting Heartbeat classifier Using ECG Morphology and Heartbeat Interval Features. Patient adapting heartbeat classifier system, a local-classifier is trained with a limited number of beat examples from the recording under test and this is then combined with a global-classifier previously trained on a large dataset. Using more beats to train the local-classifier resulted in greater performance boost although there was a diminishing return. Morphology is simple to use and most widely used by people in general. Morphology is studies are needed to identify powdered herbs.

TITLE: A rough-set-based inference engine for ECG classification

AUTHOR:B. B. Chaudhuri, et al

This paper presents rough-set theory in ECG analysis. A rule-based rough-set decision system is developed from these time-domain features to make an inference engine for disease identification. The offline-data-acquisition package is easy to create digital time databases. Decision support system information is overloaded. This is requiring more resource.

TITLE: Real-Time Discrimination of Ventricular Tachyarrhythmia with Fourier-Transform Neural Network

AUTHOR: Kei-ichiro Minami, et al

This paper presents real time discrimination of ventricular tachyarrhythmia with fourier-transform neural network. The intra cardiac electrogram method achieved high sensitivity and specificity in discrimination of supra ventricular rhythms from ventricular ones. Neutral network adapt to unknown situation. It requires high processing for large time neural network. This is large complexity of the network structure.

TITLE: Support vector machine-based expert system for reliable heartbeat recognition

AUTHOR: L.T. Hoai, et al

This paper presents a new solution to the expert system for reliable heartbeat recognition using two methods. Combining the (two methods)SVM network with these preprocessing methods yields two neural classifiers, which have been combined into one final expert system. Support vector machine algorithm is very fast and effective. SVM do not directly provide probability estimate. This is giving poor performances.

TITLE: Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network

AUTHOR: K. Minami, et al

YEAR: 1999

This paper presents Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network. The method achieved high sensitivity and specificity in discrimination of supra ventricular rhythms from ventricular ones. The potential of the authors' method for clinical uses and real-time detection was examined using human surface ECGs and intra cardiac electrograms (EGMs). Morphological is not testable and this is too much variation with in species. Problem on convergence and hybridization occurs.

III. EXISTING SYSTEM

Signal processing techniques are an obvious choice for real-time analysis of electrocardiography (ECG) signals. However, classical signal processing techniques are unable to deal with the non stationary nature of the ECG signal. In this context, this paper presents a new approach, i.e., discrete orthogonal stock well transform using discrete cosine transform for efficient representation of the ECG signal in time–frequency space. These time–frequency features are further reduced in lower dimensional space using principal component analysis, representing the morphological characteristics of the ECG signal. In addition, the dynamic features (i.e., RR-interval information) are computed and concatenated to the morphological features to constitute the final feature set, which is utilized to classify the ECG signals using support vector machine (SVM). In order to improve the classification performance, particle swarm optimization technique is employed for gradually tuning the learning parameters of the SVM classifier. In this paper, ECG data exhibiting 16 classes of the most frequently occurring arrhythmic events are taken from the benchmark MIT-BIH arrhythmia database for the validation of the proposed methodology.

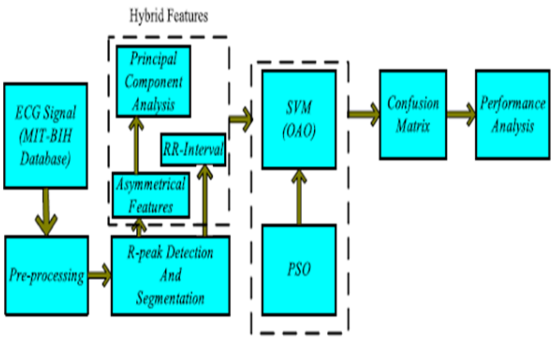

Fig 2 Existing system block diagram

The major challenges faced in this paper are the selection of appropriate R-peak detection algorithm, a new feature extraction approach that should contribute more to classification accuracy, the optimal selection of the size of feature set should take lesser training time for the classifier, and the selection of the best optimized parameters for the classifier model. This paper presents an automated ECG signal analysis scheme for long-term monitoring and analyzing the non stationary behavior of the ECG signals. A new time–frequency based feature extraction methodology is proposed yielding asymmetrical coefficients to represent the ECG signals. Further, PCA is used to reduce the feature dimensionality of the proposed asymmetrical time–frequency features. Finally, 20 projection coefficients obtained by combining the dynamic and morphological features are utilized for the prediction of 16 ECG signal classes using the SVM classifier. The parameters of the classifier are gradually tuned and optimized using PSO to yield the maximum classification performance.

The proposed method yields an improved accuracy of 98.82% on the benchmark MIT-BIH arrhythmia database. The results reported for the class-based analysis of ECG signals can be understood as a measure of performance attained if the classifier is trained using the data of patients to be examined. The future scope of this paper is to incorporate additional classes of arrhythmia signals for analysis. Further, this implementation can be used as an automated system for the analysis of ECG signals in both the online and offline modes. Since this paper is carried out at high-level compiler using a general purpose processor with sequential execution, it takes more computational time. Hence, this paper can be extended for implementation on parallel processing computing systems, FPGA and ASIC processor chip, to perform real-time analysis of ECG signals.

Feature Extraction of the Signal

The classification of cardiac arrhythmias can be achieved after extracting the features of each heart beat in the ECG signal. A good feature extraction methodology can accurately classify cardiac abnormalities. Several methods have been proposed for extracting features of one cardiac cycle. The features of one cardiac cycle may be time domain features or frequency domain features. In [1] Inan *et al.* found that morphological information along with timing information can provide high classification accuracy for larger dataset. The combining of wavelet domain feature with RR- interval features can achieve high classification accuracy as reported in [2] . The morphological feature along with the temporal feature of each patient specific data can give high classification accuracy [3]. Khazaee *et al.* [4] extracted power spectral density (PSD) features of each heart beat with three timing interval features classifying cardiac abnormalities in MIT-BIH database. The Hermit basis function can provide an effective approach for characterizing ECG heart beat and have been widely used in ECG signal classification [5]. As reported in [6], the authors Dutta *et al.* has proposed cross-correlation based feature for classifying PVC beats from non-PVC beats. They have used cross-correlation between each ECG heart beat signal with the normal heart beat signal which is chosen as reference signal.

IV. PROPOSED SYSTEM

Signal processing techniques are an obvious choice for real-time analysis of electrocardiography (ECG) signals. However, classical signal processing techniques are unable to deal with the non stationary nature of the ECG signal. In this context, this project presents a new approach, i.e., discrete orthogonal stock well transform using discrete cosine transform for efficient representation of the ECG signal in time–frequency space. These time–frequency features are further reduced in lower dimensional space using principal component analysis, representing the morphological characteristics of the ECG signal. In addition, the dynamic features (i.e., RR-interval information) are computed and concatenated to the morphological features to constitute the final feature set, which is utilized to classify the ECG signals using RBFNN based support vector machine (SVM). In order to improve the classification performance, particle swarm optimization technique is employed for gradually tuning the learning parameters of the SVM classifier. In this paper, ECG data exhibiting 16 classes of the most frequently occurring arrhythmic events are taken from the benchmark MIT-BIH arrhythmia database for the validation of the proposed methodology.

In this project, the proposed methodology used for the analysis of ECG signals consists of four stages, i.e., preprocessing, R-peak detection, feature extraction, and classification stages as shown in Fig. 5.1. The raw ECG signals are first preprocessed to remove artifacts and consequently R-peak is detected using Pan–Tompkins algorithm. Following the R-peak detection, a window is selected to extract ECG segments. Then, discrete cosine transform-based DOST (DCT-DOST) is applied to extract the morphological characteristics from each of the ECG signals. These morphological descriptors are represented in a lower dimensional space using PCA. Additionally, the dynamic features are concatenated to the morphological features, which are classified using SVM into 16 different classes of ECG signals. The RBFNN technique is employed to optimize the parameters of the SVM classifier.

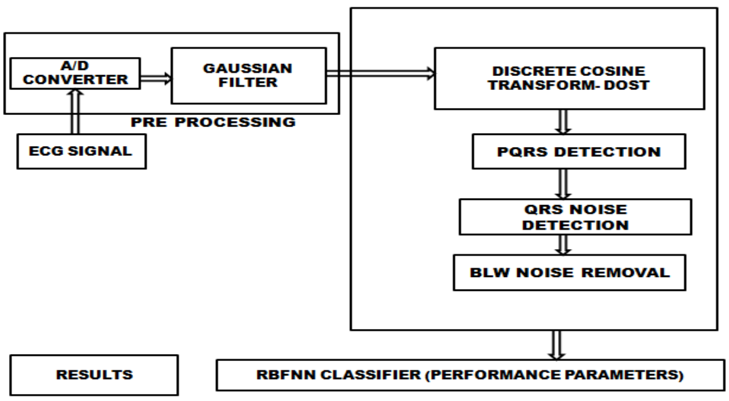

Fig 3 Proposed system block diagram

Usually, the preprocessing is done to increase the signal to- noise ratio and to eliminate various types of noise that are inherited in the ECG signals. The preprocessing step is necessary for the subsequent fiducial point detection and classification of ECG signals. The types of noise that degrade the quality of ECG signals include artifacts due to muscle contraction, power-line interference, electrode movement, and baseline wander. Therefore, a first-order derivative is employed to preprocess the raw ECG signal. The filtered ECG signal is used for further processing and analysis. For practical applications, it is necessary to detect the R-peak automatically to evaluate the proposed algorithm entirely for cardiac event diagnosis. The well-known Pan and Tompkins algorithm is employed here because it fulfills factors like robust in noise sensitivity, less computational load, and higher accuracy (i.e., 99.8%) to detect the R-peak of the subsequent ECG signals in comparison to the rest of the algorithms available.

It is provided in that the sampling rate of database is 360 Hz. In this paper, each heartbeat segment consists of 110 samples before the R peak location and 146 samples after the R peak corresponding to the pre-R segment and post-R segment, respectively, i.e., a total of 256 samples are selected to determine the length of each event corresponding to 0.712s window size. The length of fragments is selected to incorporate most of the information regarding each cardiac event. The benefit of fixing the length of each cardiac event is to locate the R-peak accurately relative to the P and T waves because they have low amplitude and are noise sensitive. The disadvantage of such segmentation can be generation of false alarms due to the shortening of two consecutive signal intervals (i.e., during faster heart rate) and the ECG segment may contain the information from the neighboring one. A DCT-based DOST (DCT-DOST) is the replacement of DFT (discrete FT) kernel of DOST with a DCT kernel. DCT is real-valued transform and is widely employed in several applications that include filtering and compression.

Due to this fact, DCT-II is most closely related to the DFT (even symmetric about $k = -1/2$) and leads to easy adaptation of the DOST algorithm. This transform is equivalent (up to an overall scale factor of 2) to a DFT of $4N$ real inputs of even symmetry where the even-indexed elements are zero. That is, it is half the DFT of the $4N$ inputs yn, where $y2n = 0$, $y2n+1 = xn$ for $0 \leq n < N$, $y2n = 0$ and $y4N-n = yn$ for $0 < n < N$. When the DCT is used, all the frequencies are positive and do not contain any negative frequencies resulting in no symmetry in the coefficients. In the SVM classification scheme, the selection of kernel function parameter is purely data dependent and chosen empirically, i.e., based on hit and trial. This paper utilizes the radial basis function (RBF) kernel for implementing SVM approach to classify the ECG signals. The RBF kernel is given by the expression as ($K(xi , x j) = \exp-\gamma \|xi-x j \|2$). The regularization parameter C and kernel function argument parameter γ of the classifier are varied in the range of [10−3, 50] and [10−3, 2], respectively, and optimized using RBFNN technique. In order to address the multiclass analysis scheme for 16 classes of ECG signals, one-against-one technique is employed in the classification phase.

V. SIMULATION RESULTS

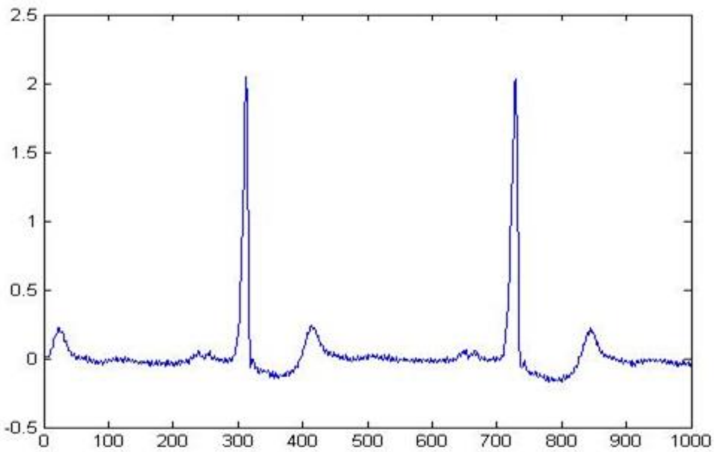

Fig 4.1 Input ECG signal

The figure 4.1 shows the input ECG signal from the different samples which are taken from BIT data. The ECG noise has reduced using Gaussian band pass filter.

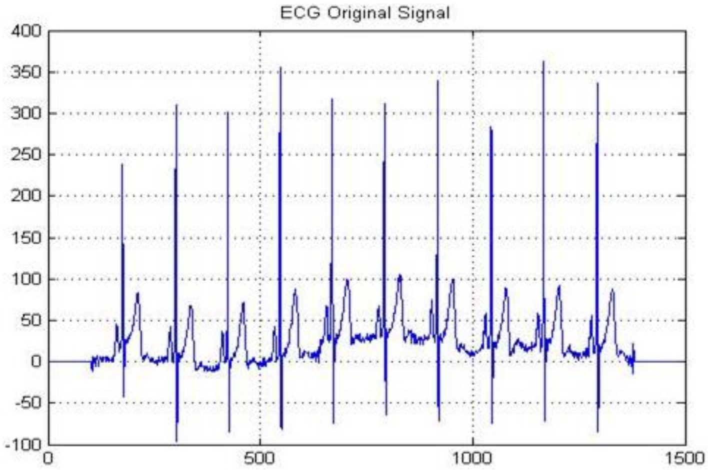

Fig 4.2 Complete ECG signal including PQRS

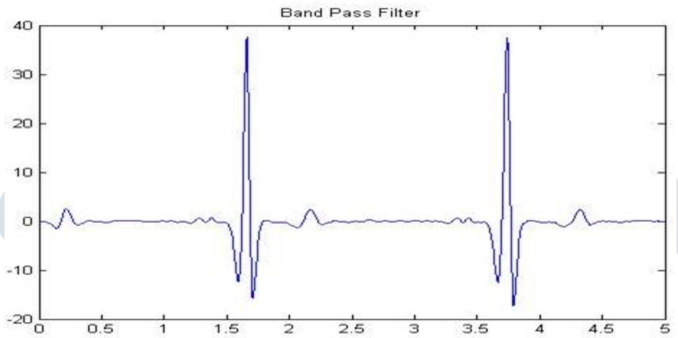

Fig 4.3 Filtered ECG signal

The figure 4.3 shows the Gaussian filter output signal. The Gaussian filter is the special hysteresis type of Band reject filter. The Acoustic noises is removed using this filter.

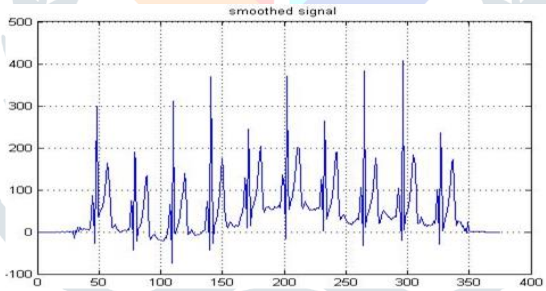

Fig 4.4 Smoothed ECG waveform using Gaussian filter.

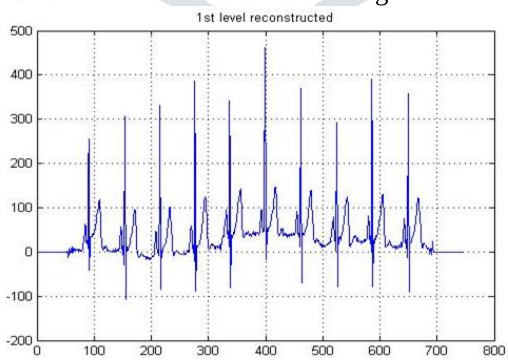

Fig 4.5 1st level reconstructed waveform

The figure 4.5 shows the 1st level reconstructed waveform using DCT-DOST waveform. From this we can get the amplitude of the signal.

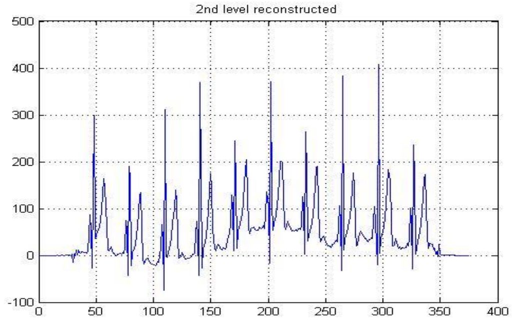

Fig 4.6 2nd level reconstructed waveform

The figure 5.7 shows the 2nd level reconstructed waveform using DCT-DOST waveform. From this we can get the amplitude of the signal.

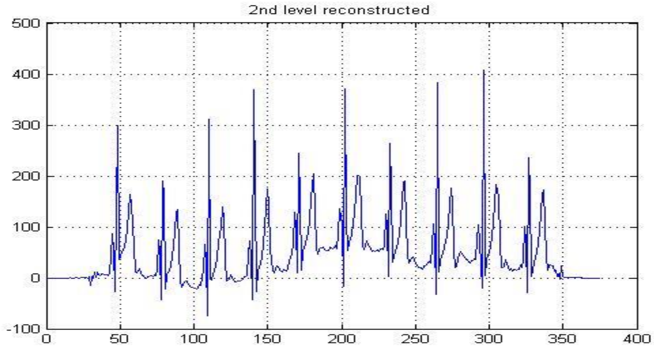

Fig 4.7 3rd level reconstructed waveform

The figure 4.7 shows the 3rd level reconstructed waveform using DCT-DOST waveform. From this we can get the amplitude of the signal.

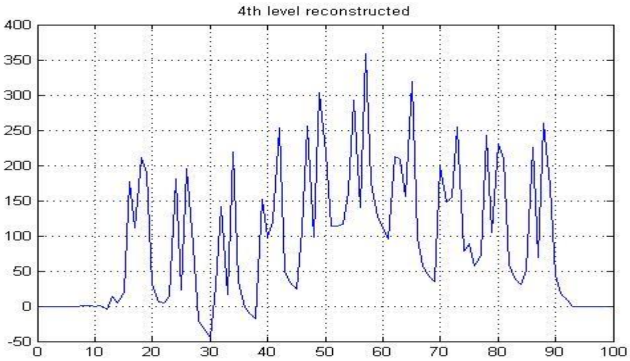

Fig 4.8 4th level reconstructed waveform

The figure 4.8 shows the 4th level reconstructed waveform using DCT-DOST waveform. From this we can get the amplitude of the signal.

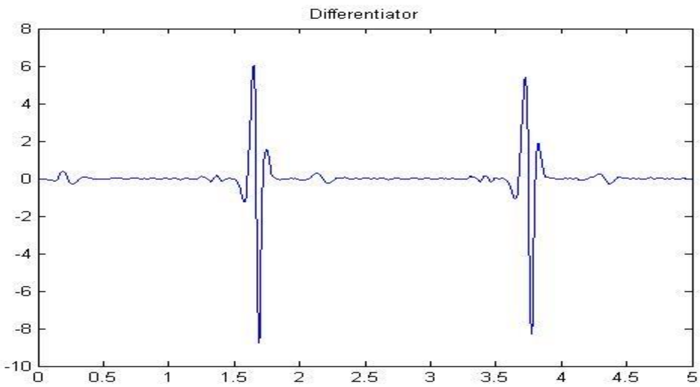

Fig 4.9 R-R interval waveform from ECG signal

The figure 4.9 shows the R-R interval waveform in the ECG signal. The differentiator will detect the R-R interval.

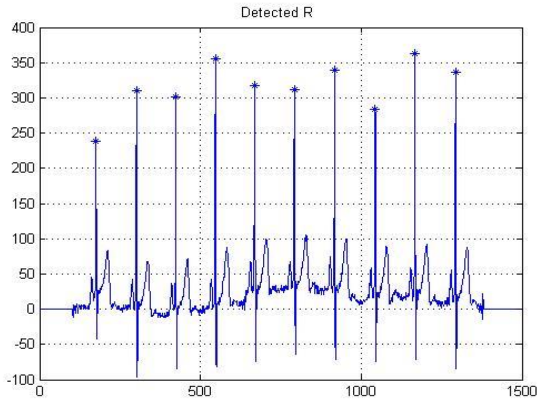

Fig 4.10 R- peak detection waveform from ECG signal

The figure 4.10 shows the R peak detection from the ECG signal. This is calculated using orthogonal transform.

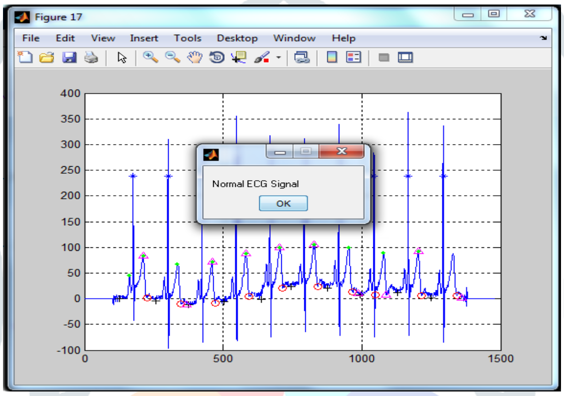

Fig 4.11 R- peak detection waveform from ECG signal

The figure 4.11 shows the R peak detection from the ECG signal. This is calculated using orthogonal transform. From this proposed SVM classifier classify the output signal. Finally the patient has normal ECG waveform.

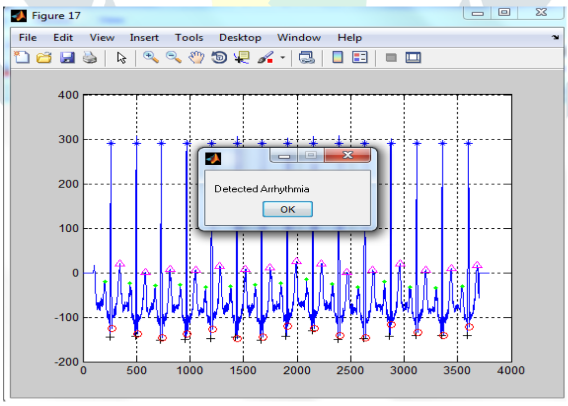

Fig 4.12 R- peak detection waveform from ECG signal for patient 1

The figure 4.12 shows the R peak detection from the ECG signal. This is calculated using orthogonal transform. From this proposed SVM classifier classify the output signal. Finally the patient has Arrhythmia ECG waveform.

VI. CONCLUSION

The ECG signal can be used as a reliable indicator of heart diseases. The MLP neural network and RBF neural network classifiers are presented as the diagnostic tool to aid the physician in the analysis of cardiac abnormalities. The most important factor in determining whether an automatic ECG diagnosis system is successful or not is depend the accuracy of event detection. The accuracy of the tools depends on several factors, such as the size and quality of the training set, the efficient extracted feature set and also the parameters chosen to represent the input. The experimental result shows that the MLP BP NN achieves sensitivity of 98.2% and 98.4% for SVEBs and VEBs respectively. For the same number of test set the RBF NN shows sensitivity 82.5% and 98.7% for SVEBs and VEBs respectively. Hence the MLP neural network shows better result as compared to RBF neural network.

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