Estimation of Heart Rate using PPG Sensor at the Suprasternal Notch

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ABSTRACT: Heart rate is an important parameter to evaluate the cardiac conditions. Initially, the heart rate was determined by placing multiple electrodes on the chest to record the electrical activity of the heart. The proposed method uses a small sized, battery operated device which is used for long term monitoring and it is feasible for home users. The recorded heart sound is corrupted by noise and it contains respiratory sound and cardiac information. The Heart Sound Segmentation and Classification Algorithm is used and it is constructed by Discrete cosine transform-Discrete orthogonal stock well transform. It is used to segment and classify cardiac cycle into S1 and S2 based on their timing characteristics. In Hilbert transform based on the transitions observed in the cardiac waveform, using one of the energy based methods, along with the utilization of the timing characteristics to reliably segment and classify the heart sounds. Here the Gaussian filter is used to eliminate the external artifacts and it is used to set the threshold and offset value. The Radial basis function neural network classifier is used to evaluate heart rate. Thus, Heart Rate is obtained with high accuracy.

Key Words: Discrete cosine transform, S1 and S2 sounds, Hilbert energy envelope, thresholding, heart rate,

I. INTRODUCTION

Heart Failure is one of the major cause of mortality in the world. Measurement of cardiac patient is carried with ECG signal. Heart Failure is a critical condition in which the heart is not able to pump enough blood to the various parts Diagnosing the heart failure earlier will prevent such progressive condition. The measured ECG signal will be affected by motion artifact and filtering of ECG signal is carried to measure heart rate without any variation.

Usage of ECG monitoring for long term cause inconvenient since it weighs heavy and many wires it is not suitable for prolonged monitoring.PPG sensor is a light weight battery operated device and consume small amount of power which is used for long term monitoring under home setting. The device operates based on this reduce the complexity The sensor is placed at the suprasternal notch and monitor the cardiac and respiration rate with single device without affected by motion artifact signal.

II. RELATED WORK

G. Chen et al, [1] PCG is a widely used method of listening to the heart sounds and indicating the presence of cardiac abnormalities. Each heart cycle consists of two and styled. Do major sounds S1 and S2 that can be used to determine the heart rate. The conventional method of acoustic signal acquisition involves placing the sound sensor at the chest where this sound is most audible. A novel algorithm for the detection of S1 and S2 heart sounds and the use of them to extract the heart rate from signals acquired by a small sensor placed at the neck. The algorithm achieves an good accuracy with respect to heart rate value provided by two commercial devices, evaluated on more than 38 h of data acquired from ten different subjects during sleep in a pilot clinical study. The largest dataset for acoustic heart sound classification and heart rate extraction in the literature to date. The same sensor and signal can be used to monitor both breathing and heart rate, making it highly useful for long-term wearable vital signs monitoring.

Z. Syed et al., [2] Skilled cardiologists perform cardiac auscultation, acquiring and interpreting heart sounds, by implicitly carrying out a sequence of steps. These include discarding clinically irrelevant beats, selectively tuning in to particular frequencies and aggregating information across time to make a diagnosis. To formalize a series of analytical stages for processing heart sounds, propose algorithms to enable computers to approximate these steps, and investigate the effectiveness of each step in extracting relevant information from actual patient data. To provide insight into the relative difficulty of the various tasks involved in the accurate interpretation of heart sounds. The framework and associated software to be useful to educators wanting to teach cardiac auscultation, and to primary care physicians, who can benefit from presentation tools for computer-assisted diagnosis of cardiac disorders. Researchers may also employ the comprehensive processing provided by our framework to develop more powerful, fully automated auscultation applications.

T.E. Chen et al., [4] The first (S1) and second (S2) heart sound recognition based only on acoustic characteristics; the assumptions of the individual durations of S1 and S2 and time intervals of S1–S2 and S2–S1 are not involved in the recognition process. The main objective is to investigate whether reliable S1 and S2 recognition performance can still be attained under situations where the duration and interval information might not be accessible.

III. PROPOSED SYSTEM

The raw ECG signals are first preprocessed to remove artifacts and consequently R-peak is detected. 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.

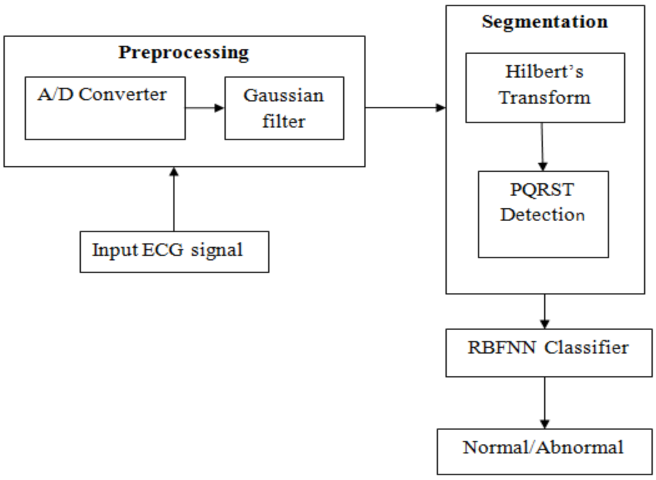

Fig 1.Proposed Block Diagram

The proposed methodology used for the analysis of ECG signals consists of four stages, they are preprocessing, R-peak detection, feature extraction, and classification stages as shown in Fig.

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, Hilberts transform 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. RBFNN Classifier segment the S1 and S2 sounds and heart beat is classified as normal and abnormal heartbeat.

A. PREPROCESSING

The 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.

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 interval and the ECG segment may contain the information from the neighboring one. A DCT-based DOST (HILBERTS) is the replacement of DFT kernel of DOST with a DCT kernel. DCT is real-valued transform and is widely employed in several applications that include filtering and compression.

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. The radial basis function (RBF) kernel for implementing SVM approach to classify the ECG signals. 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.

B. HILBERT'S TRANSFORM

The Hilbert transform of a real function, x(t) is defined as

$$x_H(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty} x(\tau)\frac{1}{t-\tau}d\tau = x(t) * \frac{1}{\pi t}$$

Therefore, function is both a time dependent function and a linear function of x(t). In fact, it is obtained from x(t), applying the convolution with (πt)^−1. Equation is obtained by filtering the signal x(t) through a linear time-invariant filter with an impulse response equal to (πt)^−1. Because the integrand has a singularity and the limits of integration are finite, the Hilbert transform is properly defined as the Cauchy principal value of the integral is 1 whenever this value exists.

C. RADIAL BASIS FUNCTION NEURAL NETWORK (RBFNN)

Radial basis function neural network (RBFNN) is a widely used pattern recognition tasks due to its fast learning algorithms. RBFNNs are nonlinear hybrid network which is a three layer structure. The input layer provides the information from the input vector to each of the nodes in the hidden layer. Each node in the hidden layer then find out the radial distance from center to each point on the associated radial basis function. Finally, each node in the output layer computes a linear combination of the activations of the hidden nodes.

The centers and widths of the RBFNN are the two parameters which can affect the classification performance.

Several methods have been proposed to find the centers of the RBFNN. Usually clustering based methods that find center locations between the input feature vector locations or some of the input feature vectors directly can be used as the centers of the neurons. The most common algorithm to determine the neuron centers of the RBFNN are the K-Means algorithm.

IV. PERFORMANCE ANALYSIS

The classification performance are analyzed on 24 records of the MIT/BIH arrhythmia database, which includes a total of 49473 beats to be classified into five heartbeat types following the AAMI convention. The 24 records are taken from the tape numbered in the range of 200–234 which contain complex ventricular, junctional, and supraventricular arrhythmias. For the classification experiments, the common part of the training dataset contains a total of 244 representative beats, including 75 from each type N, S, and V beats, and all (13) type F and (6) type Q beats, randomly sampled from each class from the first 20 records (picked from the range 100–124) of the MIT/BIH database. The patient-specific training data include the beats from the first 5 min of the corresponding patient's ECG record. Hence Patient specific feed forward MLP networks and radial basis function neural networks are trained with a total of 244 common training beats and along with first 5 min of the corresponding patient's ECG record. The remaining beats (25 min) of 24 records, which contains pathological cases are completely new to the classifier, and are used as test patterns for performance evaluation

V. RESULTS AND DISCUSSION

INPUT ECG SIGNAL

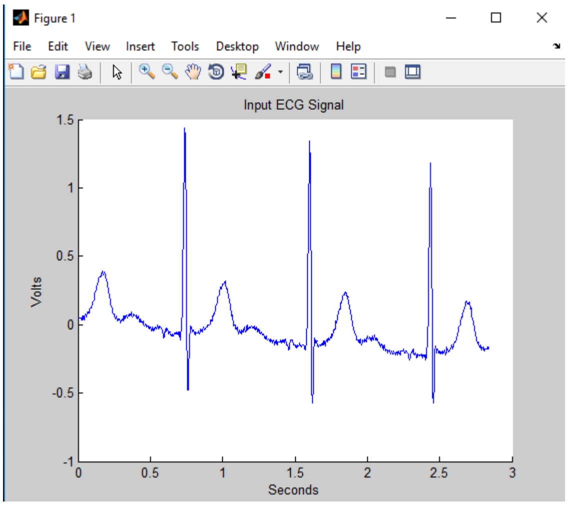

Fig 2.Input ECG Signal

The Fig 2. shows the input ECG signal from the different samples

FILTER OUTPUT

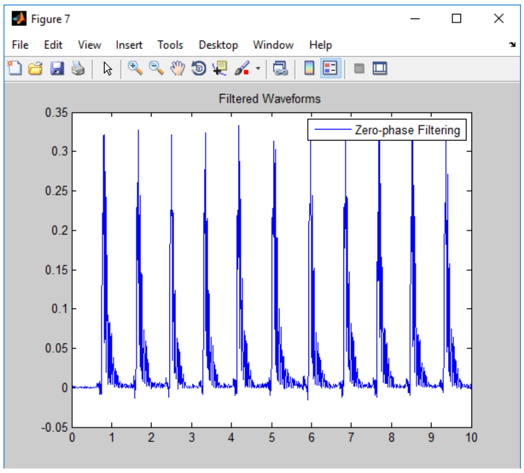

Fig 3.Input ECG signal after Filtering

The Gaussian filter is the special hysteresis type of Band reject filter. The filter with a window length of 5 samples is used to remove the impulsive spikes and smoothen the signal. Hence, the recording is performed in an uncontrolled environment, it is easily possible for the acoustic sensor to saturate due to sounds such as speech, snoring, swallowing, coughing, etc

HILBERT WAVEFORM

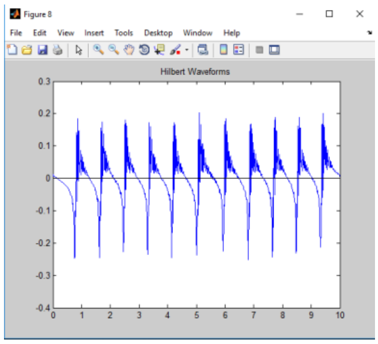

Fig 4.ECG Signal after applying Hilbert Waveform

Fig 4. Shows the Zero phase Hilbert Waveform determine the zero point of the ECG signal, which gives the information about one zero point to another zero point.

R PEAK DETECTION

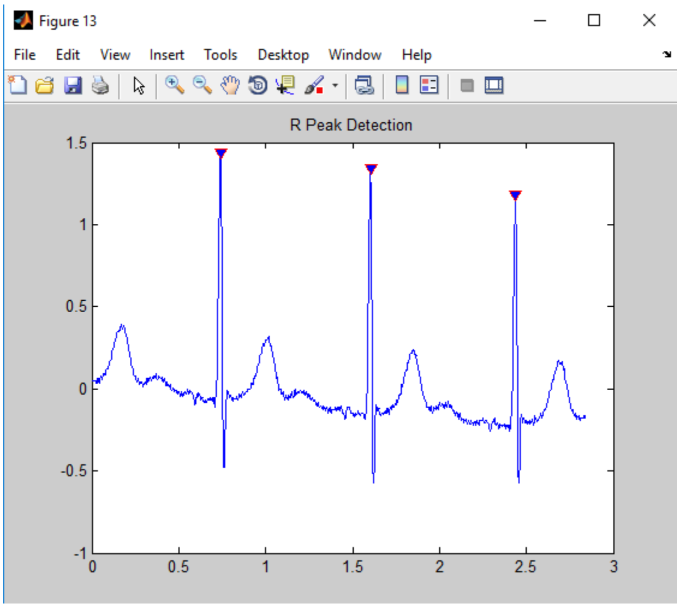

Fig 5.R Peak detection of ECG Signal

R-R peak detection

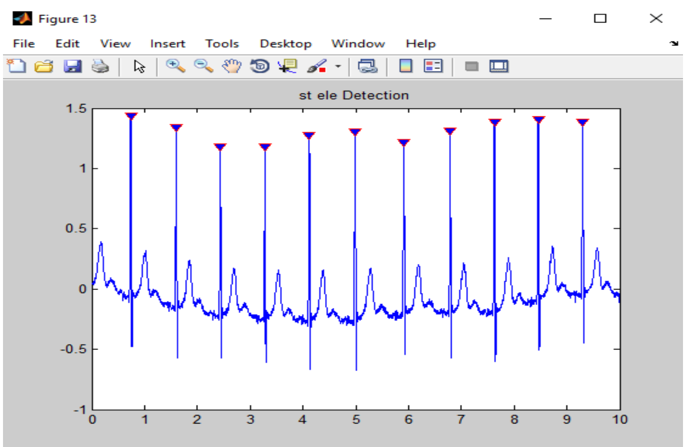

Fig 6.R-R Peak Detection of ECG Signal

Fig 5 and Fig 6 shows the R peak detection from the ECG signal. This is calculated using orthogonal transform, the pre RR interval is defined as the RR interval between a given heartbeat and the previous heartbeat. The RR interval between a given heartbeat and the following heartbeat is known as post RR interval

MESSAGE BOX

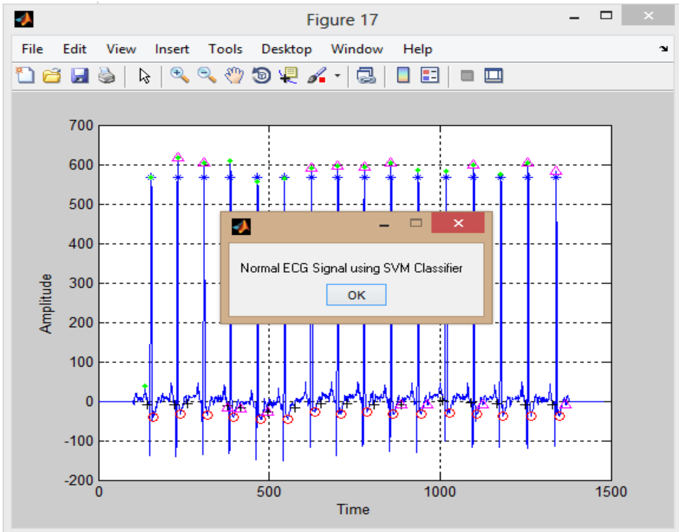

Fig.7 Normal ECG signal

The Fig 7 shows the normal ECG signal. This is calculated using orthogonal transform. From this proposed SVM classifier classify the output signal. Now the corresponding patient has normal ECG waveform

PERFORMANCE ANALYSIS

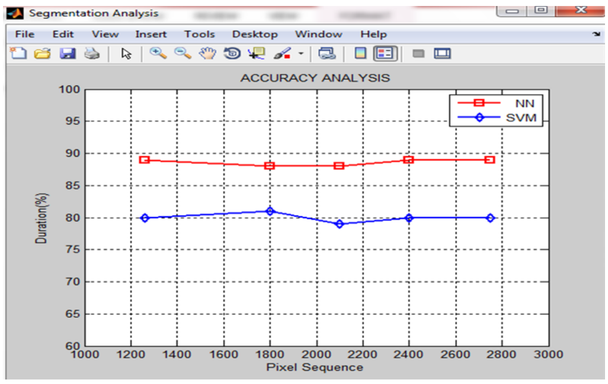

Fig.8 Accuracy Analysis of SVM and RBFN classifier

Fig.8 shows the comparison of SVM Classifier with RBFN Classifier and 90% accuracy is obtained in the proposed system.

VI. CONCLUSION

The Heart Rate at the suprasternal notch of a subject not only provides significant information about the breathing sounds but also allows for a possible auscultation of the cardiac sounds. The Heart Sound Segmentation and Classification Algorithm is used and it is constructed by Discrete cosine transform-Discrete orthogonal stock well transform algorithm to segment and classify the heart sounds collected from the suprasternal notch is presented, which is then used to extract the heart rate. The proposed algorithm is capable of evaluating the heart rate reliably from the suprasternal notch over long-term monitoring. An automated analysis of multiple physiological parameters from acoustic signals acquired at a single auscultation site and provides an advanced usage of the wearable device as compared to the conventional use of a sensor on chest. Furthermore, since the proposed algorithm eliminate the use of any site bound signal characteristics, the methodology was also tested on the heart sounds gathered from the suprasternal notch .The complexity of the algorithm is reduced using proposed algorithm that involves the automatic segmentation of S1 and S2 sounds and heart rate is determined with high accuracy.

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