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# Automatic Arrhythmia Detection and Classification using Wavelet Transform and Support Vector Machines

Hementh S K
Dept. of Electronics and Communication
Younus College of engineering and technology
Kollam, India

Nishil A
Assistant Professor
Dept. of Electronics and Communication
Younus College of engineering and technology
Kollam, India

***Abstract*—Arrhythmias are the abnormalities in the heart beats. In this paper an improved method for Automatic detection and classification of arrhythmias. Here the methods used for the detection and classification are adaptive filtering methods, wavelet transforms and support vector machines. The input given to the system is ECG signals. The MIT-BIH ECG database and Arrhythmia database and also some collected ECG data are utilized to test the methods. The detection and classification based on PP, RR, and QRS intervals. By using this methods we can classify different arrhythmias accurately. It have better efficiency than other methods.**

***IndexTerms — ECG (Electrocardiograph), Arrhythmia Classification, Adaptive Weiner filtering, Adaptive LMS filter, Wavelet Transform, SVM (Support Vector Machine)***

## I. INTRODUCTION

Now a days Cardiac diseases are the major reason for the death of many peoples. In Most of the cases these diseases are not identified in the right time. So the detection of these cardio vascular diseases are very important. Cardiac arrhythmias are irregular beating of hearts. Electro cardio gram is the simplest method to identify different types of heart diseases. The SA node generates the electrical impulses that controls the rhythm of heart beat. Any disturbances in this rhythm leads to the condition known as arrhythmia. Normally these are identified from the ECG signals. This paper presents an automatic identification method of cardiac arrhythmias.

Another method of arrhythmias identification are also discussed in this paper. Different algorithms are proposed for better identification and classification [2]. But several drawbacks have been noted such as lesser efficiency and poor performance. A wide variety of detection algorithms have been developed based on temporal/morphological [4], spectral or complexity parameters extracted from the ECG signal.The combination of ECG parameters using machine learning techniques [9], such us neural networks or support vector machines (SVM), has been suggested as a useful approach to improve the detection efficiency.

In this proposed approach different methods are used for the detection and classification of arrhythmias. This method includes the preprocessing of collected ECG signals[3], peak and interval detection using wavelet transform and classification of arrhythmias with support vector machine classifier. The different peaks of ECG signal ie. P, Q, R, S and different intervals such as RR interval, PR interval and QRS Complex have been found out.

The rest of the section is discussed as follows: Section 2 explains about different methods and methodologies used. And in section 3, experimental results and different output is shown. Finally the section 4 includes the conclusion of the proposed system.

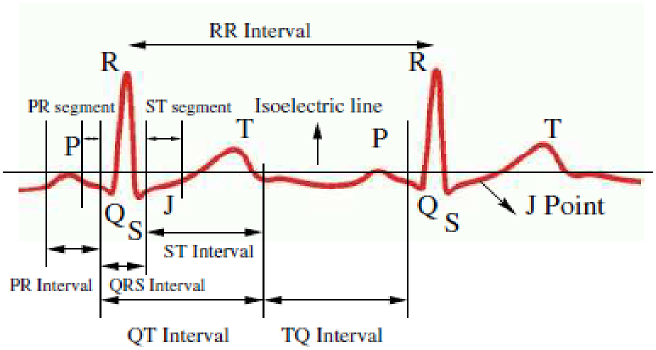



Fig 1. ECG signal

## II. PROPOSED METHODS

This section illustrates the different process and steps for the detection and classification of arrhythmias.

### *A. Overview*

The proposed method includes ECG data collection, Preprocessing, Peak detection and interval detection using Wavelet transform and SVM Classifier for arrhythmia classification. Figure 2 shows the block diagram of proposed method.

In this paper the following arrhythmia categories are considered: Hypocalcaemia, Tachycardia, Bradycardia, Sudden cardiac arrest, Dextrocardia and Hyperkalaemia.

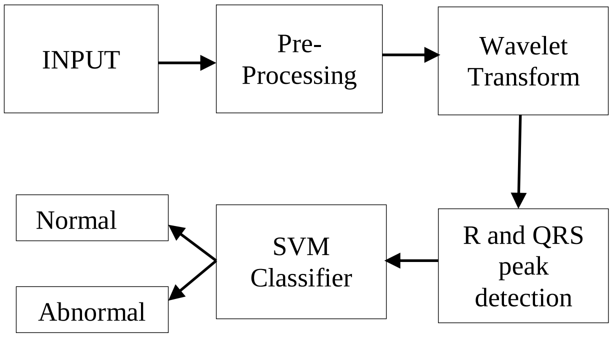



Fig 2. Block diagram of proposed method

The ECG signal is characterized by five peaks and valleys denoted by the letters P, Q, R, S, T.The performance of ECG analyzing system depends mainly on the accurate and reliable detection of the QRS complex as well as T- and P waves. By knowing the normal interval and peak amplitude of different peaks in ECG signal, the signals can be classified into different types by this proposed method. The normal values are given below.

| | |
|---|---|
| Amplitude | P-wave — 0.25 mV |
| | R-wave — 1.60 mV |
| | Q-wave — 25% R wave |
| | T-wave — 0.1 to 0.5 mV |
| Duration | P-R interval: 0.12 to 0.20 s |
| | Q-T interval: 0.35 to 0.44 s |
| | S-T interval: 0.05 to 0.15 s |
| | P-wave interval: 0.11 s |
| | QRS interval: 0.09 s |

### B. *ECG Collection*

Different ECG data andArrhythmia database collected from the MIT/BIH database available at the physionet had been sampled at 250 Hz [6].

### C. *Preprocessing*

There are many types of noises present in the ECG signals, such as Baseline Wander (BW), Powerline Interference (PLI), Electromyogram (EMG) and Motion artifact (MA). All these noises results in an incorrect prediction of heart activities. Thus noise cancellation is mainly included in the preprocessing stage. Several adaptive filtering methods can be used to reduce these type of noise. NLMS (Normalized Least Mean Square) Adaptive filtering and Adaptive Weiner filtering are the most effective methods.

The adaptive Weiner filtering can be used in many signal enhancement methods. The basic idea behind the Weiner filtering is to obtain an estimate of noise free signal from the corrupted signal with different noises. This can be done by minimizing the mean square error between the desired noise free signal and the estimated signal. The transfer function of the filter in frequency domain is given as

$$H(\omega)=\frac{Pd(\omega)}{Pd(\omega)+Pn(\omega)} \qquad (1)$$

Where $P_d(\omega)$ and $P_n(\omega)$ are the power spectral densities of desired and noise signals respectively. The signal to noise ration can be defined as

$$SNR = \frac{Pd(\omega)}{Pn(\omega)} \qquad (2)$$

Signal to noise ratio can be incorporated as

$$H(\omega) = [1+\frac{1}{SNR}]^{-1} \qquad (3)$$

LMS adaptive filtering can also be used for the noise cancellation in the ECG signal [14]. It also utilizes least mean square method instead of minimum mean square as both of them are similar in nature. The least mean square value of the error has been found out in LMS algorithm.

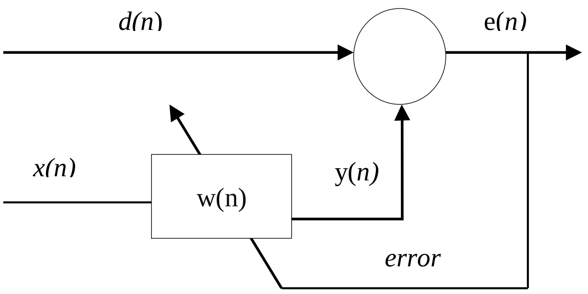



Fig 3. Adaptive filter structure

Fig 3 shows the adaptive filter structure with *x(n)* as input sequence and *d(n)* as the desired signal which is the combination of a signal which is corrupted by noise signals, *w(n)*, the weight of the filter updated by some relations

$$w(n+1) =w(n)+\mu x(n)e(n) \qquad (4)$$

*e(n)* is the filter error which is given by

$$e(n) = d(n)-x(n) \qquad (5)$$

Weiner filters are linear least square estimators. Both NLMS and Weiner adaptive filtering can be used. But there are some advantages of using adaptive Weiner filtering. They can also be applied in the frequency domain. Signal to noise ratio can be improved by using adaptive Weiner filter

### D. *Wavelet Transform*

R-R Peak and QRS complex detection is important for the identification and classification of different types of arrhythmias. Here wavelet transform is used to identify the different peaks present in an ECG signal [5]. Previously Fourier analysis method is checked to identify these peaks. Fourier transform based analysis cannot be used in the case of biomedical signals since they are non-stationary. Wavelet transformation is a continuous operation that divides its signal into different components appearing at different scales. Itis essential to have time frequency components with varying time sets to analyze the signal in different sizes. The transform is computed at various locations and scales of the signal, thus filling up the transform plane.

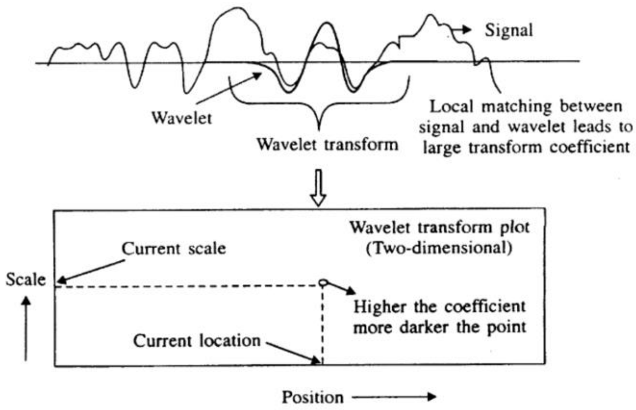



Fig 4. Signal, wavelet and transform

$\psi(t)$ be a real or complex valued function

$$\psi_{a,b}(t) = \frac{1}{|\sqrt{a}|}\,\psi(\frac{t-b}{a}) \qquad (6)$$

Where$b$ is location parameter and $a$is scaling parameter. Awavelet transform coefficient, representing how much the scaled wavelet is similar to the function at location t = (b/a).

Wavelet transform may be given as

$$\mathrm{W(t)}=\int_t f(t)\frac{1}{|\sqrt{a}|}\,\psi(\frac{t-b}{a})\,dt \qquad (7)$$

The value $\frac{1}{\sqrt{a}}$ maintains the energy constant for all values of a. It can have different values such as positive and negative, if a>1 then the wavelet function is stretched along the time axis. a<1 wavelet function contracts and 'a' is negative function turn over in the time axis.

### *E. Feature Extraction*

Feature extraction process is done to get the different characteristics of an ECG signal. The extraction mainly includes the detection and identification of different peaks and QRS complex. The classification of arrhythmias are completely based on the different intervals between peaks and amplitudes. Wavelet transform based method is used here to obtain these peaks. Another method known as Pan Tompkins algorithm has also been utilized to detect the peaks. Pan Tompkins algorithm is a real time QRS detection algorithm where a series of filters were used. But in this method it is something different from Pan Tompkins algorithm.

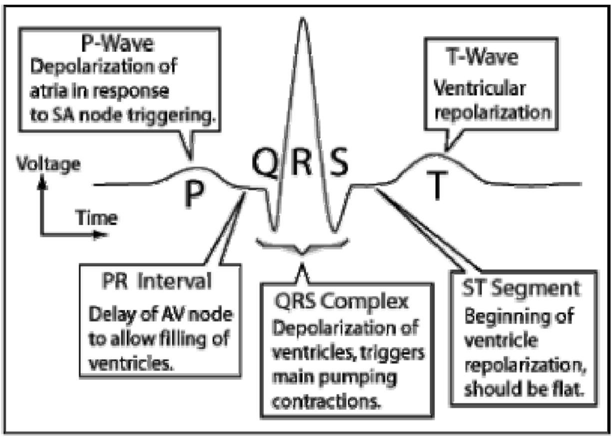



Fig 5. Peaks and QRS complex

The analysis starts from detecting the QRS waveform. The R wave peak is then determined for a maximal value point by searching the interval corresponding before and after the QRS detection mark. Q wave, the first inflection point prior to the R wave is identified by a change in the sign of slope, zero slope, or a significant change in slope. A low pass digital filter is used for noisy ECG signals to smoothen the data before calculating the slope. The isoelectric line of the ECG can be measured by searching between the P and Q waves interval near-zero slope. In order to determine the QRS duration; the S point is positioned as the first inflection point after R wave using the same strategy for the Q wave. Measurements of the QRS duration, R-peak magnitude relative to the isoelectric line, and the RR interval are then determined.The classificatn of arrhythmias has been obtained based on the RR interval, QRS width and diff peak values.

### *F. Arrhythmia Classification*

The last stage is the classification different types of arrhythmia based on the different features extracted from the ECG signal. This classification can be done with the help of SVM (Support Vector Machine) classifier.It also, has the potential to handle very large feature spaces and large classification problems. SVMs have been applied on many

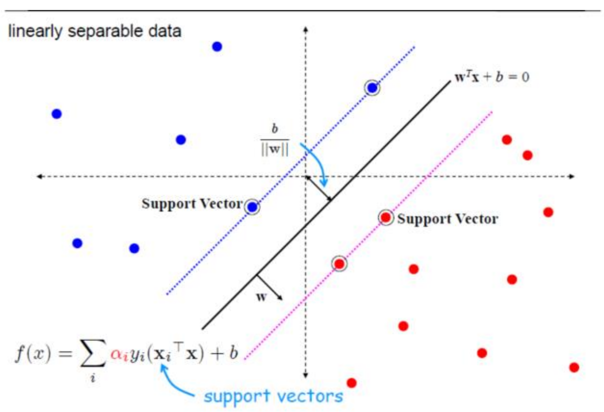



Fig 6. Support vector machine representation

fields, such as text classification, image classification, and bioinformatics and so on.

Consider S = $\{(x_i, y_i)\}_{i=1}^{n}$ is set known as training set where n is the number of input samples $x_i$ is an m-dimensional input vector, and $y_i$ is the label of $x_i$ .A support vector machine generates a hyperplane or set of hyperplanes in an infinite-dimensional space. A hyper plane can be defined as

$$f(x)= w^T x+b \qquad (8)$$

Where $w$ is th m dimensional vector and $b$ is the scalar. Based on these functions, can create some decisions. And the decision function given by

$$D(S) = \text{sign}\ (w^T x+b)$$

$$= \text{sign}\ ( \textstyle\sum_{i \in U} \alpha_i y_i x_i^T x + b) \qquad (9)$$

Where $\alpha_i$ is the non-negative LaGrange's multiplier.

## III. EXPERIMENTAL RESULTS

### A. *Performance*

The performance parameters are defined using four measures such as True Positive, True Negative, False Positive and False Negative.

True Positive (TP) is when the arrhythmia detection is coincides with decision of physician

True Negative (TN) is when both classifier and physician suggested absence of arrhythmia

False Positive (FP)is when system labels a healthy case as an arrhythmia one

False Negative (FN)is when system labels an arrhythmia as healthy

These measures helps to calculate accuracy, positive predictive, sensitivity and specificity of the system. Accuracy is the ratio of number of correctly classified signals. Sensitivity defined as rate of correctly classified positive. It should be high for a good classifier. Specificity defined as the rate of correctly classified negative. Positive predictive defined as the probability that disease is present when test is positive.

Accuracy= (TP+TN) / N

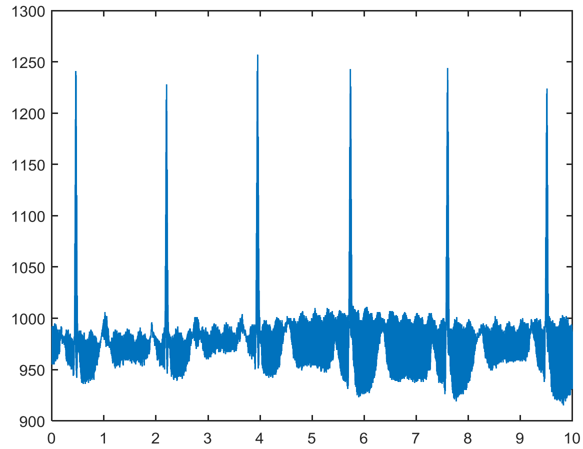
Sensitivity = TP / (TP+FN)

Specificity = TN/ (TN+FP)

Positive predictive =TP / (TP+FP)

By using this system we get good accuracy and better performance. Different arrhythmias are classified with an accuracy ranges from 91 % to 97 %.

### B. *Graphical Analysis*



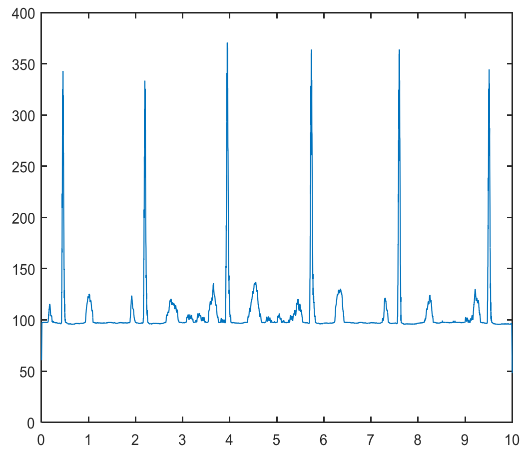




Fig 7. Input ECG signal affected by different noises
Fig 8. Signal after preprocessing

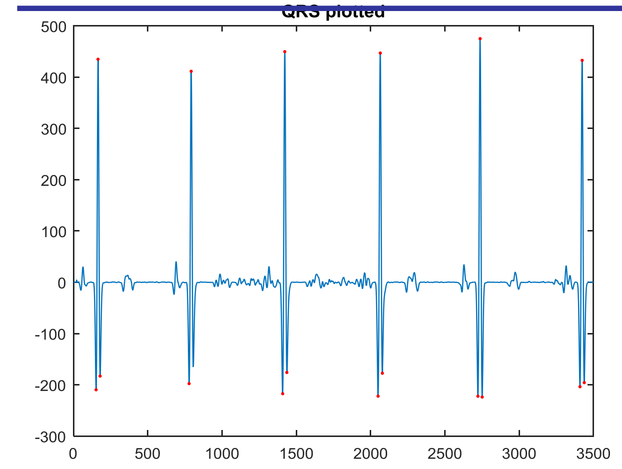



Fig 9. QRS detected from given ECG Signal

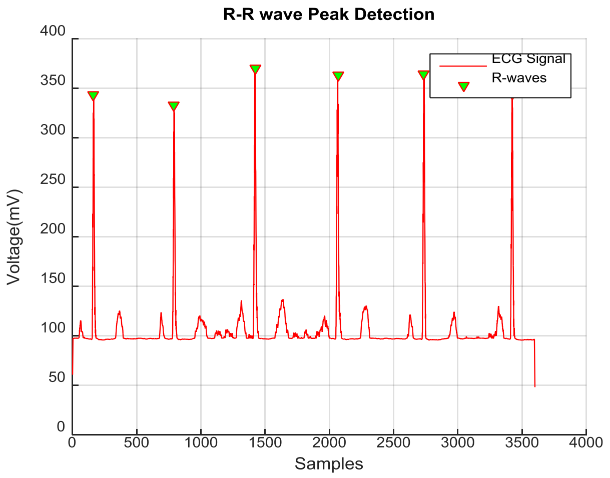



Fig 10. RR peak detected from the ECG signal

| S. No. | Name of abnormality | Characteristic features |
|---|---|---|
| 1 | Tachycardia | R-R interval <0.6 s |
| 2 | Bradycardia | R-R interval >1 s |
| 3 | Hypercalcaemia | QRS interval <0.1 s |
| 4 | Dextrocardia | Inverted P-wave |
| 5 | Myocardial ischaemia | Inverted T-wave |
| 6 | Sinoatrial block | Complete drop out of a cardiac cycle |
| 7 | Hyperkalemia | Tall T-wave and absence of P-wave |
| 8 | Sudden cardiac death | Irregular ECG |

Table 1.different arrhythmias and characteristic results

## IV. DISCUSSIONAND CONCLUSIONS

Abnormalities in the ECG depend upon detection factors of change in amplitude and duration, or appearing noise. This method gives an Effective and flexible software tool using Mat lab for ECG arrhythmia detection. In this paper (“Automatic Arrhythmia Detection and Classification Using Wavelet Transform and Support Vector Machines”), we have proposed a highly efficient and highly accurate method to detect and classify different cardiac arrhythmias. The probability of occurring of manual error can be reduced by this method. The proposed system is very fast in execution and having very simple steps. In this study, it has been shown that the use of SVM algorithms combining ECG features significantly improves the efficiency for the detection of life-threatening arrhythmias. As a modification, many real time sensors can be introduced into the system and real time accuracy can be improved. Further modification can be made to develop a real time hardware system that can be utilized by common peoples within their homes.

The proposed method achieved accuracy above 98 % sensitivity 94% thereby the overall efficiency is also improved compared to other methods. Adaptive methods are used in preprocessing stage to remove the noises effectively. So this method proposes highly efficient noise free technique which can be used for arrhythmia detection and classification.

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