

Performance Analysis of SVM Based Arrhythmia Classification

S. Abarna and V. Amudha

St. Peters College of Engineering and Technology, Avadi, India

Abstract: The ECG signals are analyzed for the detection of various arrhythmia conditions of the heart. Each and every point in the signal is a characteristic feature of electrical activity of the heart. Such features from the ECG signal are to be isolated for the efficient detection of a particular disease. Such extraction of the fiducial points from the ECG signal is done by using Pan Tompkins algorithm. MITBIH database helps in providing different types of signal for different arrhythmia conditions. The output is classified by using support vector machine enabling the automated evaluation.

Key words: Arrhythmia · Cardiac activity · QRS complex · Pan Tompkins algorithm

INTRODUCTION

Electrocardiography (ECG or EKG) is meant for recording the cardiac electrical activity. This acquisition is the interpretation of the transthoracic region by means of electrodes that are attached to the surface of the skin and recorded over a period of time. ECG recording are done by both invasive and non invasive methods. The non invasive recording of these signals is termed as ECG or EKG where as invasive method is done by using implantable loop recorder. [1]The heart beats due to the control of electrical impulses. This rhythmic impulse helps in contraction and relaxation of the heart muscle thereby pumping blood to different organs. Sometimes the normal rhythm gets disturbed due to blockages in the conduction pathways or formation of unwanted pulsating regions. Under such conditions the heart may beat too fast, too slow or irregularly. All such irregularities in the heart rhythm are also called arrhythmias or Dysrhythmias [2]. Most cardiac arrhythmias are harmless, however, some arrhythmias can be very serious and life threatening. Thus these ECG wave form is the result of polarization and depolarization of cardiac tissue. Each and every characteristic of the ECG signal corresponds to a particular cardiac activity. Abnormalities and arrhythmia conditions can be detected by studying the ECG signal. The normal ECG signal is shown in fig 1.

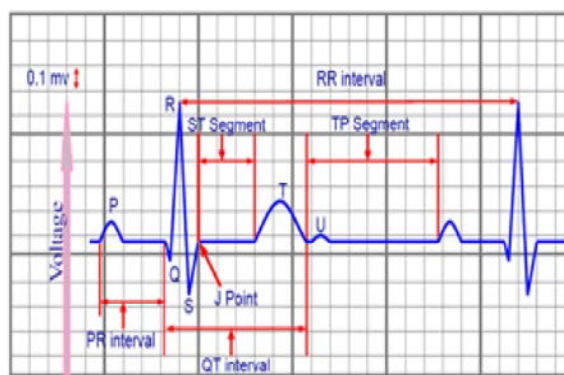


Fig. 1: A normal ECG signal.

Various techniques are used to isolate the ECG signal. Techniques such as derivative thresholding, wavelet transform, time plane method, etc are in convention to measure and isolate the ECG signal. Pan Tompkins algorithm is efficient for the measurement of fiducial points of the ECG signal. The pan Tompkins algorithm involves a preprocessing of the signal together with isolation of the ECG signal. This algorithm uses a series of operation such filtering, differentiating, thresholding etc to remove muscle interference noises, base line wander and character detection. MITBIH database [3] helps in providing different types of signal for different arrhythmia conditions.

Literature Review: A simple method of QRS detection is obtained by allowing the signal to pass through the threshold. Thus the P and T waves suppressed leaving behind the QRS complex. The QRS complex itself is enough for the detection of certain arrhythmia conditions such as Sudden Cardiac Death (SCA). To isolate the various characteristics of an ECG signal derivative methods such as Pan Tomkins algorithm has to be used [4]. The improved version of Pan Tompkins algorithm is presented which helps in the accurate calculation of heart rate even in slow-moving state, providing wider sampling rate and effective avoiding of finite word-length effect during calculation in float type. This will lead to the better isolation of the ECG signal avoiding muscle interferences, breathing interferences and noises [5].

The heart rate variability is also a main characteristic measurement of quantifying the autonomic cardiac activity. The results are compared by means of wavelet analysis and Pan Tompkins algorithm. The wavelet based method helps in cleaning the signal from various kinds of distortion. Both time domain analysis and frequency domain analysis of HRV are presented for the identification of the arrhythmia condition [6].

Automated removal of cardiac interference from EEG signal is presented. While acquiring the EEG signal the common interference is the cardiac activity. It is impossible to acquire the EEG signal without ECG interferences and thus Pan Tomkins algorithm is used to isolate these ECG signals. The QRS peaks in ECG are identified, without assuming periodicity. Signals that consist of only QRS peaks and zero-lines are computed. Linear regression of the EEG channels is performed on the "QRS signals" remove cardiac interference [7]

Algorithm

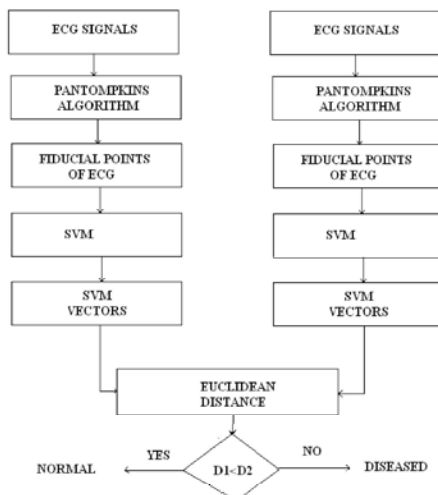


Fig. 2: Block diagram

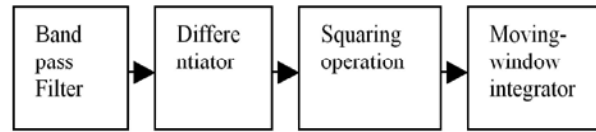


Fig. 2: Block diagram of Pan Tompkins algorithm.

Pantompkins Algorithm: The Pan Tompkins algorithm helps in identifying the various morphological characteristics of the ECG signal. QRS detection is based on slope, amplitude and width of the QRS complexes. The block diagram is given in fig 2.

The signal is acquired from the MITBIH database. It undergoes the series of processes such as filtering, differentiating, squaring and integrating. [4] The signal is first passed through a band pass filter, where the low pass and high pass filter are cascaded. IIR filters are used with a gain of 3 db. The pass band is 5-12 Hz, which is enough to isolate the essential characteristics. The filtering is done to remove the noises, muscle interferences and breathing interferences. This also reduces frequency interference, including the baseline trends. While doing this operation the filtered signal is delayed by 21 samples.

The second step is to pass the signal through the differentiator where the high sloped signals are enhanced and the signals with lower slopes are suppressed. Thus QRS signals are enhanced while noises and other signals are suppressed.

The third step involves in squaring of the obtained values, where the negative values are made positive.

The signal is now integrated by using a moving window integrator. This will result in a hump shaped signal which will correspond to the QRS complex of the ECG signal. By the usage of the logical functions and the slope thresholds, a signal containing a unit rectangular window at the location of the QRS complexes are obtained. Now the signal is gated with this rectangular pulse signal to find the maximum peak. This becomes the R peak of the ECG signal.

The minimum point that lies between the rising edge of the pulse and the R peak provides the Q point. The S point is calculated by using the minimum point between the R peak and the falling edge of the ECG signal. The falling and the rising edges of the pulses are used to find the time difference between the QRS complex indicating the onset and offset of the QRS complex. The P wave and T wave are found by suppressing the QRS complex since these waves are not as sharp as QRS. Hence the slope is also minimum. This is done by applying a masking gate signal. The remaining highest peaks in the signal are the P and the T waves of the ECG signals [8].

Support Vector Machine: The purpose of Support Vector classification is to devise a computationally efficient way of learning good separating hyperplanes in a high dimensional feature space. The SVM works in the high dimensional feature space formed by the nonlinear mapping, $\phi(x)$ of the n-dimensional input vector into a K-dimensional feature space. The equation of the hyperplane separating two different classes is given by the relation

$$y(x) = W^T \phi(X) = \sum_{j=1}^K \omega_j \omega_j(x) + \omega_o = 0$$

with $w = [\omega_0, \omega_1, \dots, \omega_k]^T$ is the weight vector of the network.

By introducing the so-called Lagrange multipliers, the learning task of SVM is reduced to quadratic programming. On account of these facts, there exist many highly effective learning algorithms, which result in the global minimum of the cost function and the best possible choice of the parameters of the neural network. And all operations in learning and testing are done using so-called kernel functions. The kernel is defined as $K(x, x') = \phi^T(x) \phi(x')$. In this paper, a radial basis function (RBF) was selected as the kernel and the parameters – kernel width σ and margin-losses trade-off C , which provided best classification, were fixed by experiments before learning. Simultaneously, the learning of SVM can be referred to as the separation of learning vectors x_i into two classes of the destination values either $d_i=1$ or $d_i=-1$, with maximal separation margin.

Implementation: The algorithm is implemented on MATLAB platform. The signal is selected from the MITBIH database which contains sample signals for arrhythmia and diseased conditions. The steps involving the analysis of pan Tompkins algorithm are given as follows

- Step 1: Select the signal.
- Step 2: Band pass the signal.
- Step 3: Pass the signal into a differentiator.
- Step 4: Square the resulting signal
- Step 5: Pass it into a moving window operator.
- Step 6: Threshold and average the signal.
- Step 7: Measure and indent the fiducial points.

The fiducial points indicating the morphological characteristics are obtained [10].

RESULTS AND CONCLUSION

Thus the important morphological features are isolated by using this algorithm given in fig 3.

By knowing the QRS width, RR interval, R peak amplitude, P amplitude, S amplitude, T amplitude different arrhythmias can be identified compared with the standard parameter values in hand. The results are tabulated in table 1.

While considering a particular disease condition such as atrial fibrillation, the success percentage can be calculated by performing the same algorithm on different signals that are available in the database. A table that indicates the success rates is calculated by using the table 2.

The atrial fibrillation is an arrhythmia condition where the atrium contraction is minimum. This is due to

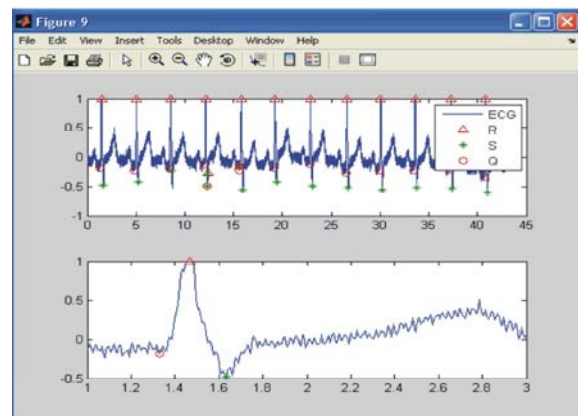


Fig. 3: Detection of the fiducial points of an ECG signal.

Table 1: Measurement of fiducial points

Disease Condition	P Amplitude (m volts)	R Amplitude (m volts)	S Amplitude (m volts)	RR Interval (m sec)	QRS Width (m sec)	T Amplitude (m volts)
Normal	0.25	1	-0.5	3	0.4	0.2
Sudden cardiac death	0.1-0.5	0.5-0.7	-0.4	0.5	0.6	0.5
Heart attack	0.5	0.9	-0.1	5	0.3	0.3
Myocardial infarction	0.	0.6-0.8	-0.3	4	0.03	0.6
Coronary heart disease	-0.1	0.4	-0.1	0.5	0.01	0.1
Atrial fibrillation	0.02	1	0.01	0.8	0.15	0.02
Angina	0.15	0.8	-0.1	0.6	0.1	0.2
Cardiac myopathy	-0.2	0.5	-1	2	0.08	0.2

Table 2: Analysis of Atrial fibrillation

Atrial fibrillation	P amplitude (m volts)	R amplitude (m volts)	S amplitude (m volts)	RR interval (m sec)	QRS width (m sec)	T amplitude (m volts)
Signal 1	0.02	1	0.01	0.8	0.12	0.02
Signal 2	0.018	1	0.02	0.71	0.17	0.18
Signal 3	0.019	0.9	0.02	0.81	0.139	0.177

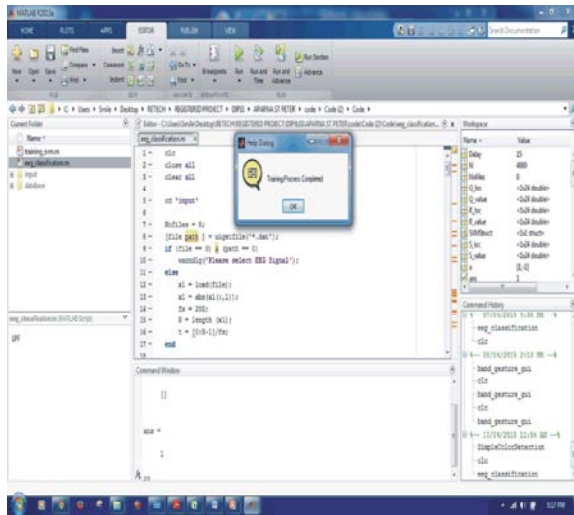


Fig. 5: Training of SVM

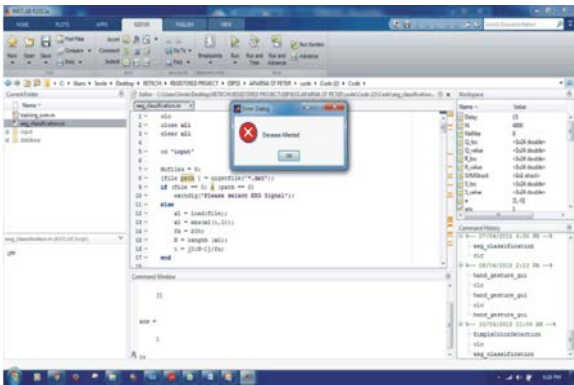


Fig. 6: Result from SVM

the improper conduction of electrical impulses by the muscles of the atrium. Thus gravitation is factor contributing to the flow of blood into the ventricle leaving behind the 30% of the blood into auricle. Thus backflow may result collapsing the entire circuit. The patients having this disease have a decreased value of P wave, since P wave corresponds to the atrial fibrillation.

Thus the manual calculation provides fair satisfactory results in identifying the arrhythmia conditions.

The process of automated detection involves in identification of normal and the diseased ECG. This process is done by support vector machine.

Future Work: The results that are calculated by the Pan Tompkins algorithm help in finding the various fiducial points indicating the morphological characteristics of the heart. The values that are calculated by using the algorithm help in analyzing on the type of arrhythmia conditions to which it belongs to. Improvements can be made by adopting automatic evaluation of the ECG signal in detecting the arrhythmia condition. Support vector machine identifies the normal and the diseased successfully with greater accuracy. Improvements are to be made to evaluate with various disease condition.

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