A Novel SVM Neural Network Based Clinical Diagnosis of Cardiac Rhythm

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Abstract

The cardiovascular disease is one of main disease that threatens the human life. There are many ways to find cardiac arrhythmia. Electrocardiogram (ECG) is a key diagnostic tool to monitor and visualize the electrical activity of heart and is used to study its normal or abnormal functioning. Physicians perform routine diagnosis the functioning of heart by visually examining the shapes of ECG waveform. However, automatic processing and classification of ECG data would be extremely useful in patient monitoring and telemedicine systems. Such real time applications require techniques that are highly accurate and very efficient. A new method for arrhythmia classification for clinical diagnosis is proposed in this project.ECG signal being one of the most analyzed for well being humans. The analysis of electrical activity of heart is done on ambulatory for ICU.For diagnosis, efficient methods are required to classify and exact arrhythmia. In this paper we are proposing a new method and approach by which the ECG arrhythmia is classified based on support vector machine (SVM).

Keywords—*Electrocardiogram, support vector machine, arrhythmia*

I. INTRODUCTION

ECG is the electrical activity of the heart over a period of time as detected by electrodes attached to the outer surface of the skin and recorded by a device external to the body. The recording produced by this noninvasive procedure is termed as ECG. An ECG test records the electrical activity of the heart.ECG is used to measure the rate and regularity of heartbeats, as well as the size and position of the chambers, the presence of any damage to the heart. The information thus obtained can be used to discover different types of heart diseases. A typical ECG tracing of the cardiac cycle (heartbeat) is shown in fig.1 which consists of a P wave, a QRS complex, a T wave, and a U wave which is normally visible in ECG.

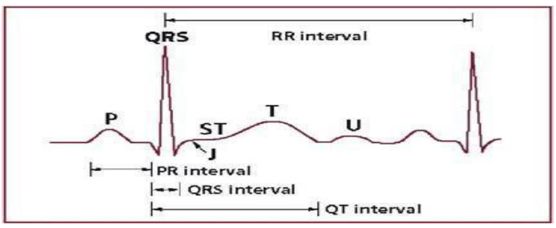

Fig 1: Waves and Intervals

The P wave is the first wave of the electrocardiogram. It represents the spread of electrical impulse through the atrial musculature (activation or depolarization). During normal atrial depolarization, the main electrical vector is directed from the sino-atrial node towards the atrio-ventricular node, and spreads from the right atrium to the left atrium. This turns into the P wave on the ECG. Absence of the P wave indicates atrial fibrillation, sino-atrial block, and A-V nodal rhythm. Its duration of not more than 0.11 seconds and amplitude of not more than 3mm in height and gently rounded, not pointed or notched. The duration of the P wave is 80ms.

The most important complex in the ECG is the QRS. It represents the spread of the electrical impulse through the ventricular muscle (depolarization).The QRS complex reflects the rapid depolarization of the right and left ventricles. They have a large muscle mass compared to the atria and so the QRS complex usually has much larger amplitude than the P-wave. The duration of the QRS complex is 80 to 120 ms.

The T wave represents the repolarization of the ventricles. The normal shape of the T wave is slightly rounded and slightly asymmetrical. The interval from the beginning of the QRS complex to the apex of the T wave is referred to as the absolute refractory period. The last half of the T wave is referred to as the relative refractory period. The duration of the T wave is 160 ms.

The ST segment connects the QRS complex and the T wave. The point at which it begins is called J (junction) point. The ST segment represents the period when the ventricles are depolarized. The duration of the ST segment is 80 to 120 ms. The ST segment is important in the diagnosis of ventricular ischemia because under those conditions, the ST segment can become either depressed or elevated.

The PR interval is measured from the beginning of the P wave to the beginning of the QRS complex. The PR interval reflects the time the electrical impulse takes to travel from the sinus node through the AV node and entering the ventricles. The duration of the PR wave is 120 to 200 ms.

The interval between R wave and the next R wave is the inverse of the heart rate. Normal resting heart rate is between 50 and 100 beats per minute. RR intervals are normally regular, but may be irregular with sinus node disease and ventricular arrhythmias. Its normal duration is from 0.6s to 1.2 s.

II. PROBLEM DESCRIPTION

A. Functions of Heart

The heart provides a continuous blood circulation through the cardiac cycle and is one of the most vital organs in the human body. The heart is divided into four main chambers: the two upper chambers are called the left and right atria (singular atrium) and two lower chambers are called the right and left ventricles. The right-hand side of the heart receives de-oxygenated blood from the body tissues (from the upper- and lower-body via the Superior Vena Cava and the Inferior Vena Cava, respectively) into the right atrium. This de-oxygenated blood passes through the tricuspid valve into the right ventricle. This blood is then pumped under higher pressure from the right ventricle to the lungs via the pulmonary artery. The left-hand side of the heart receives oxygenated blood from the lungs (via the pulmonary veins) into the left atrium. This oxygenated blood then passes through the bicuspid valve into the left ventricle. It is then pumped to the aorta under greater pressure (as explained below). This higher pressure ensures that the oxygenated blood leaving the heart via the aorta is effectively delivered to other parts of the body via the vascular system of blood vessels is shown in fig 2.

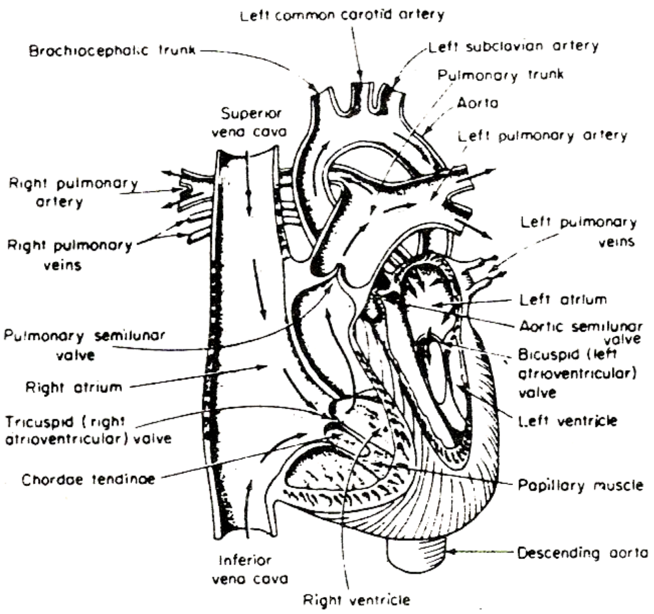

Fig 2: Functions of Heart

B. Noises present in the ECG signal:

1) Power line interference

It consists of 50-60Hz pickup and harmonics, which can be modeled as sinusoids. Characteristics, which might need to be varied in a model of power line noise, of 60Hz component (as most of the signals of study were digitized in USA) include the amplitude and frequency content of the signal. The amplitude varies up to 50 percent of the peak to peak ECG amplitude.

2) Electrode contact noise

It is a transient interference caused by loss of contact between the electrode and the skin that effectively disconnects the measurement system from the subject. The loss of contact can be permanent, or can be intermittent as would be the case when a loose electrode is brought in and out of contact with the skin as a result of movements and vibration. This switching action at the measurement system input can result in large artifacts since the ECG signal is usually capacitively coupled to the system. It can be modeled as randomly occurring rapid base line transition, which decays exponentially to the base line value and has a superimposed 60Hz component.

3) Motion Artifacts

Motion artifacts are transient base line changes caused by changes in the electrode-skin impedance with electrode motion. As this impedance changes, the ECG amplifier sees a different source impedance which forms a voltage divider with the amplifier input impedance. Source impedance changes as the electrode position changes. The peak amplitude and duration of the artifact are variable, This type of interference represents an abrupt shift in base line due to movement of the patient while the ECG is being recorded

4) Muscle contraction

Muscle contractions cause artifactual mill volt level potentials to be generated. The base line electromyogram is usually in the microvolt range and therefore is usually insignificant. The maximum noise level is formed by adding random single precision numbers of 50% of the ECG maximum amplitude to the uncorrupted ECG. A plot of the ECG is corrupted by electromyographic noise.

5) Base Line Drift with Respiration

The drift of the base line with respiration can be represented by a sinusoidal component at the frequency of respiration added to the ECG signal. The amplitude and the frequency of the sinusoidal component should be variables. The variations could be reproduced by amplitude modulation of the ECG by the sinusoidal component added to the base line.

6) Instrumentation Noise Generated by Electronic Devices

The parameter detection algorithms cannot correct artifacts generated by electronic devices. The input amplifier saturates and no information about the ECG reaches the detector. In this case manual preventive and corrective action needs to be undertaken.

*7) **Electrosurgical noise***

It completely destroys the ECG and can be represented by a large amplitude sinusoid with frequencies approximately between 100 KHz to 1MHz. Since the sampling rate of an ECG signals 250 to 1000Hz an aliased version of the signal.

C. Types of Diseases:

*1) **Bradycardia***

Bradycardia often starts in the sinus node. It is a sinus rhythm with a resting heart rate of 50 beats per minute or less. A slow heart rate may occur because the sinus node discharges electrical impulses at a slower rate than normal. Due to the reduction in heart rate R-R interval becomes greater than 1.5s and the P waves are found to be wider as shown in fig 3.

Fig 3: Bradycardia

2) Tachycardia

Tachycardia is the heart rate which exceeds the normal rate over 100 beats per minute, with at least three irregular heartbeats in a row. It originates from the Sino-atrial (SA) node, near the base of the superior vena cava. The R-R interval is less than 0.5s as shown in fig 4. Because of this there won't be sufficient blood flow to heart.

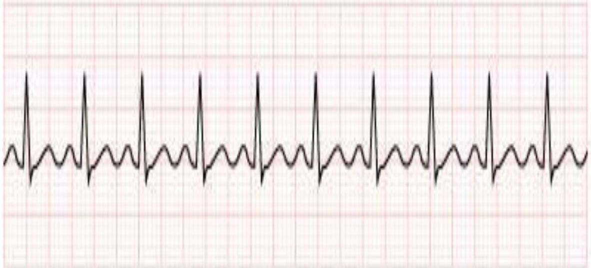

Fig 4: Tachycardia

3) Ventricular Fibrillation

Ventricular fibrillation is a condition, in which there is uncoordinated contraction of the cardiac muscle of the ventricles in the heart. When it occurs in the lower chambers of the heart, it is called ventricular fibrillation. During ventricular fibrillation, blood is not removed from the heart. There may be lack of QRS complex in the ECG signal as shown in fig 5.

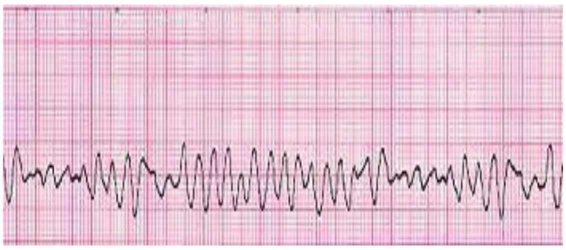

Fig 5: V Entricular Fibrillation

4) Atrial Flutter

Atrial flutter (AFL) is an abnormal heart rhythm that occurs in the atria of the heart. It is caused by chaotic electrical impulses in the atria of the heart. The AV node and the ventricles (the two lower chambers) are therefore bombarded with frequent, irregular electrical impulses as shown in fig 6.

Fig 6: Atrial Flutter

5) Sinus Arrhythmia

Sinus arrhythmia is an irregular cardiac rhythm in which the heart rate usually increases during inspiration and decreases during expiration as shown in Fig 7.

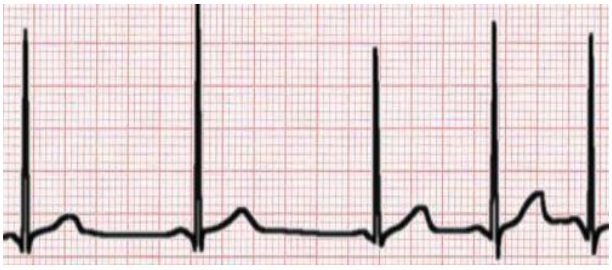

Fig 7: Sinus Arrhythmia

6) Premature Ventricular Contraction

It is a relatively common event where the heartbeat is initiated by the heart ventricles rather by the Sino atrial node, the normal beat initiator. The QRS and T waves look very different to normal readings. The Premature ventricular contraction is as shown in fig 8.

Fig 8: Premature Ventricular Contraction

7) Myocardial Infraction

Myocardial infraction, commonly known as a heart attack, is the irreversible necrosis of heart muscle secondary to prolonged ischemia. This usually results from an imbalance in oxygen supply and demand, which is most often caused by plaque rupture with thrombus formation in a coronary vessel, resulting in an acute reduction of blood supply to a portion of the myocardium. It is characterized by the absence of Q and S waves.

8) Heart Block

Complete heart block occurs when the electrical signal can't pass normally from the atria, the heart's upper chambers, to the ventricles, or lower chambers. If the atrio-ventricular (AV) node is damaged during surgery, complete heart block may result. Patients with third degree heart block are at high risk of ventricular standstill and sudden cardiac death. P waves are not conducted to the ventricles because of block at the AV node.

9) Mitral Stenosis

Mitral stenosis is a heart valve disorder that involves the mitral valve. This valve separates the upper and lower chambers on the left side of the heart. The upper heart chamber swells as pressure builds up. Blood may flow back into the lungs. Fluid then collects in the lung tissue, making it hard to breathe. It is characterized by absence of P, Q and long S wave.

III. SOFTWARE DESCRIPTION

MATLAB is a numerical computing environment and fourth-generation programming language. Developed by Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and FORTRAN. Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the symbolic engine, allowing access to symbolic computing capabilities. An additional package, Simulink, adds graphical multi-domain simulation and Model-Based Design for dynamic and embedded systems. MATLAB is widely used in academic and research institutions as well as industrial enterprises.

We consider each of the characteristics in our training set as a different dimension in some space, and take the value an observation has for this characteristic to be its coordinate in that dimension, so getting a set of points in space. We can then consider the similarity of two points to be the distance between them in this space under some appropriate metric.

The way in which the algorithm decides which of the points from the training set are similar enough to be considered when choosing the class to predict for a new observation is to pick the k closest data points to the new observation, and to take the most common class among these.

1. A positive integer k is specified, along with a new sample
2. We select the k entries in our database which are closest to the new sample
3. We find the most common classification of these entries
4. This is the classification we give to the new sample.

Artificial Neural Network (ANN) classifiers are usually trained on a training set to re-adjust the weights of the connections between the units inside the network as shown in fig 9. The output layer of a neural network has a unit oj for each possible class, and given an instance xi we predict the class Yj corresponding to the unit which gives the highest value. We expect that, the more conforming an instance is for its class, the higher the corresponding oj value would be. As proposed in, we can build a CP based on ANNs (ANN-CP), using the non-conformity measure defined in αi = 1 − ot, αi =maxj=1,...,c:j6=t oj ⁄ ot

Instead of designing an algorithm, one could construct an example data Set and an error criterion, and train ANNs to perform the desired input output mapping.ANNs can be highly nonlinear; the amount of nonlinearity can be influenced by design, but also depends on the training data.

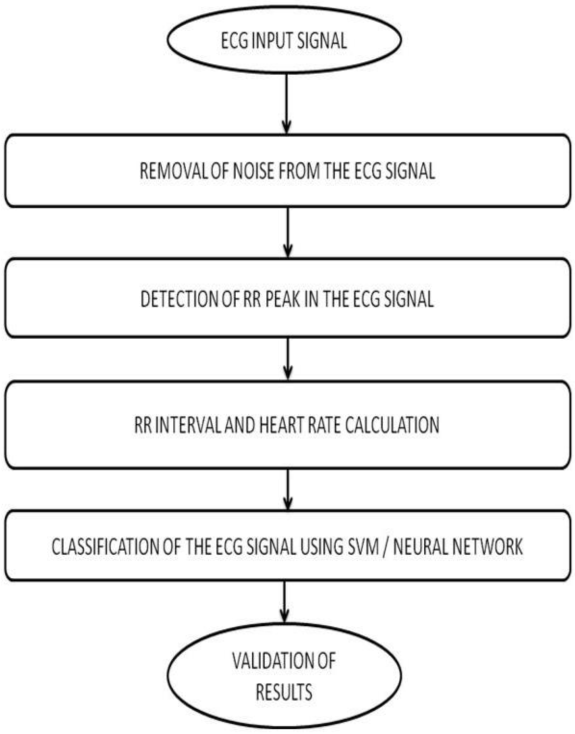

Fig 9: A Feed-Forward ANN for a Three-Class Classification Problem

IV. SYSTEM DESIGN

In this paper I have implemented a novel method based on SVM to classify the ECG signal into normal and abnormal beats. The general Block diagram of a ECG processing system is given in fig 10.

For classification we use machine learning approach. Machine learning is the science of getting computers to act without being explicitly programmed. In the past decade, machine learning has given us self-driving cars, practical speech recognition, effective web search, and a vastly improved understanding of the human genome.

Supervised learning is the machine learning task of inferring a function from labeled training data. The training data consist of a set of training examples. In supervised learning, each example is a pair consisting of an input object (typically a vector) and a desired output value (also called the supervisory signal).A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples.

The support vector machine (SVM) is a supervised learning method that generates input-output mapping functions from a set of labeled training data. The mapping function can be either a classification function, i.e., the category of the input data, or a regression function. For classification, nonlinear kernel functions are often used to transform input data to a high-dimensional feature space in which the input data become more separable compared to the original input space. Maximum-margin hyper planes are then created. The model thus produced depends on only a subset of the training data near the class boundaries. Similarly, the model produced by Support Vector Regression ignores any training data that is sufficiently close to the model prediction. SVMs are also said to belong to “kernel methods”. In addition to its solid mathematical foundation in statistical learning theory, SVMs have demonstrated highly competitive performance in numerous real-world applications, such as bioinformatics, text mining, face recognition, and image processing, which has established SVMs as one of the state-of- the-art tools for machine learning and data mining, along with other soft computing techniques, e.g., neural networks and fuzzy systems.

SVM (Support Vector Machine) definition Viewing input data as two sets of vectors in an n-dimensional space, a SVM will construct a separating hyper plane in that space, which maximizes the margin between the two data sets .

For implementing SVM on image classification, we are given a certain number p of training data, each data has two parts: the n-dimensional vector of image features and the corresponding labels of data (either 1 or - 1)

$$S = \{(x_i , y_i) \mid x_i \in \Re^n , y_i \in \{-1,1\}\}_{i=1}^{p}$$

Each x_i is a n-dimensional vector. SVM want to give out the maximum-margin hyper plane dividing the objects with label (y_i) = 1 from those with label = - 1.

V. RESULT AND CONCLUSION

A. *Extraction of Various Features of the ECG:*

The extraction of various features of ECG waveform has been given in the fig 9.

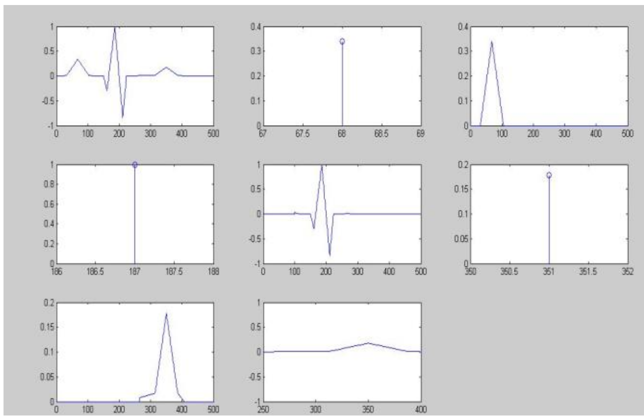

Fig 11: Features of ECG

B. *RR Interval and Heart Rate of the ECG Signal:*

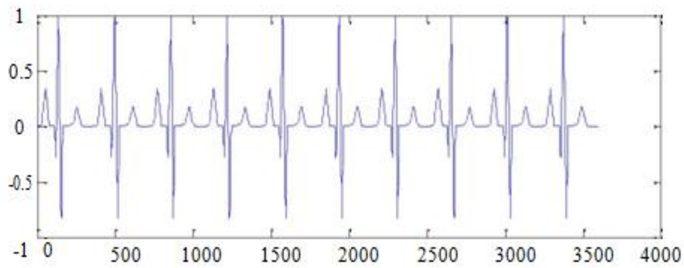

Fig 12: Detection of R peak

Training Data:

0.97	1.1	normal
0.97	1.2	normal
0.88	0.33	abnormal
0.89	0.34	abnormal
0.88	0.3	abnormal
1	0.18	abnormal
1	0.17	abnormal
0.85	0.2	abnormal
0.84	0.27	abnormal
0.82	0.27	abnormal
0.83	0.18	abnormal

C. *Results obtained using SVM Classifier:*

[0.8000]	[0.9000]	'normal'
[0.8900]	[0.9500]	'normal'
[0.8800]	[1]	'normal'
[1]	[1]	'normal'
[0.8200]	[0.8700]	'normal'
[0.8300]	[0.8500]	'normal'
[0.9000]	[0.9500]	'normal'
[0.9000]	[0.9100]	'normal'
[1]	[0.8600]	'normal'
[0.9200]	[0.8800]	'normal'
[1]	[1.4000]	'normal'
[1]	[1.5000]	'normal'
[1]	[1.5500]	'normal'
[0.9200]	[1.4000]	'normal'
[0.9500]	[1.3000]	'normal'
[0.9500]	[1.6000]	'normal'
[1.9400]	[1.4000]	'normal'
[1]	[1.3500]	'normal'
[1]	[1.3600]	'normal'
[0.9700]	[1.3000]	'normal'
[0.9700]	[1.1000]	'normal'
[0.9700]	[1.2000]	'normal'
[0.8900]	[0.3400]	'abnormal'
[0.8800]	[0.3000]	'abnormal'
[1]	[0.1800]	'abnormal'
[1]	[0.1700]	'abnormal'
[0.8500]	[0.2000]	'abnormal'
[0.8400]	[0.2700]	'abnormal'
[0.8200]	[0.2700]	'abnormal'

AMPLITUDE	HEART RATE	TYPE NORMAL/ABNORMAL ECG
0.88	0.9	Normal
0.89	0.95	Normal
0.88	1	Normal
1	1	Normal
1	0.97	Normal
0.85	0.91	Normal
0.84	0.9	Normal
0.82	0.87	Normal
0.83	0.85	Normal
0.9	0.95	Normal
0.9	0.91	Normal
1	0.86	Normal
0.92	0.88	Normal
1	1.4	Normal
1	1.5	Normal
1	1.55	Normal

[0.8300]	[0.1800]	'abnormal'
[0.9000]	[0.1600]	'abnormal'

[0.9000]	[0.1700]	'abnormal'
[1]	[0.1600]	'abnormal'
[0.9700]	[0.2000]	'abnormal'
[0.9000]	[0.2500]	'abnormal'
[0.9600]	[0.2500]	'abnormal'
[0.8200]	[0.3100]	'abnormal'
[0.9000]	[0.3300]	'abnormal'
[0.8600]	[0.3200]	'abnormal'

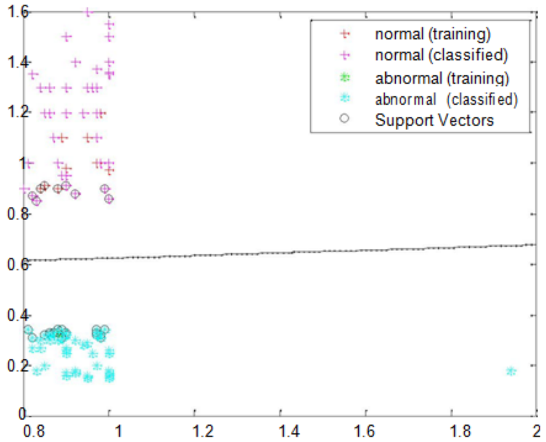

Fig 13: SVM Trained Data and Classification of ECG Signal

In this paper a new methodology for the classification of ECG signal is proposed and implemented using MATLAB. The proposed method classifies the normal and abnormal beat based on the RR interval. For the extraction of RR internal and Heart rate calculation a method is used which was based on adaptive thresholding. The program is universal to all sampling frequencies and calculates the heart rate. The observed data is given as input to the SVM and the classification was found to be accurate.

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