CLASSIFICATION OF ECG ARRHYTHMIAS USING BAYESIAN CLASSIFIER

Chaitanya Jambotkar
Jain College of Engineering & Research

ISSN (Online): 2455-7838

SJIF Impact Factor : 6.093

EPRA International Journal of

Research & Development

(IJRD)

Monthly Peer Reviewed & Indexed
International Online Journal

Volume: 4, Issue:1, January 2019

Published By
EPRA Publishing

SJIF Impact Factor: 6.093 Volume: 4 | Issue: 1 | January | 2019 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Peer Reviewed Journal

CLASSIFICATION OF ECG ARRHYTHMIAS USING BAYESIAN CLASSIFIER

Pooja M Kagalkar [1]
[1] 8th SEM Student in Department of Electrical and Electronics Engineering, K.L.E.I.T, Hubli, Karnataka, India.

Asst. Prof. Chaitanya K Jambotkar[2]
[2]Assistant Professor in Department of Electrical and Electronics Engineering, K.L.E.I.T, Hubli, Karnataka, India.

ABSTRACT

An electrocardiogram (ECG) is a bioelectrical signal which records the heart's electrical activity versus time. ECG arrhythmia can be defined as any of a group of conditions in which the electrical activity of the heart is irregular and can cause heartbeat to be slow or fast. It can take place in a healthy heart and be of minimal consequence, but they may also indicate a serious problem that leads to stroke or sudden cardiac death. The analysis is carried using ECG signals available in the MIT-BIH Arrhythmia database, since the signal contains some noise and an artifact having which it is not adequate for further process, hence pre-processing of ECG signal is of great importance. The pre-processing of ECG signal is carried out with help of Wavelet toolbox wherein SNR of ECG signal is improved by de-noising the signal from baseline wandering, high frequency and low frequency noise. The Min-Max algorithm is applied for identification of R-peak and also other peak in the ECG signal. The MATLAB Wavelet toolbox is also used for feature extraction of ECG signal. Bayesian classifier is used to classify the input dataset into normal or abnormal ECG signal. Then ECG signal is classified into different classes of Arrhythmia.

INDEX TERMS: *Renewable energy sources, Energy Management System, Smart system, Conserving energy.*

I. INTRODUCTION

Electrocardiography (ECG or EKG abbreviated from the German Elektrokardiogramm) is the recording of the electrical activity of the heart. Traditionally this is in the form of a transthoracic (across the thorax or chest) interpretation of the electrical activity of the heart over a period of time, as detected by electrodes attached to the surface of the skin and recorded or displayed by a device external to the body. The recording produced by this noninvasive procedure is termed an electrocardiogram (also ECG or EKG). It is possible to record ECGs invasively using an implantable loop recorder.

An ECG is used to measure the heart’s electrical conduction system. It picks up electrical impulses generated by the polarization and depolarization of cardiac tissue and translates into a waveform. The waveform is then 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, and the effects of drugs or devices used to regulate the heart, such as a pacemaker.

Most ECGs are performed for diagnostic or research purposes on human hearts, but may also be performed on animals, usually for diagnosis of heart abnormalities or research.

The ECG device detects and amplifies the tiny electrical changes on the skin that are caused when the heart muscle depolarizes during each heartbeat. At rest, each heart muscle cell has a negative charge, called the membrane potential, across its cell membrane. Decreasing this negative charge toward zero, via the influx of the positive cations, Na^+ and Ca^{++}, is called depolarization, which activates the mechanisms in the cell that cause it to contract. During each heartbeat, a healthy heart will have an orderly progression of a wave of depolarization that is triggered by the cells in the sinoatrial node, spreads out through the atrium, and passes through the atrioventricular node and then spreads all over the ventricles. This is detected as tiny rises and falls in the voltage between two electrodes placed either side of the heart, which is displayed as a wavy line either on a screen or on paper. This display indicates the overall rhythm of the heart and weaknesses in different parts of the heart muscle.

Usually, more than two electrodes are used, and they can be combined into a number of pairs (For example: left arm (LA), right arm (RA), and left leg (LL) electrodes form the three pairs LA+RA, LA+LL, and RA+LL). The output from each pair is known as a lead. Each lead looks at the heart from a different angle. Different types of ECGs can be referred to by the number of leads that are recorded, for example 3-lead, 5-lead, or 12-lead ECGs (sometimes simply "a 12-lead"). A 12-lead ECG is one in which 12 different electrical signals are recorded at approximately the same time and will often be used as a one-off recording of an ECG, traditionally printed out as a paper copy. Three- and 5-lead ECGs tend to be monitored continuously and viewed only on the screen of an appropriate monitoring device, for example during an operation or whilst being transported in an ambulance. There may or may not be any permanent record of a 3- or 5-lead ECG, depending on the equipment used.

The heart is a muscular pump made up of four chambers. The two upper chambers are called atria, and the two lower chambers are called ventricles. A natural electrical system causes the heart muscle to contract and pump blood through the heart to the lungs and the rest of the body.

II. MORPHOLOGICAL PARAMETERS OF ECG SIGNAL

A typical ECG tracing of the cardiac cycle (heartbeat) consists of a P wave, a QRS complex, a T wave, and a U wave, which is normally invisible in 50 to 75% of ECGs because it is hidden by the T wave and upcoming new P wave. The baseline of the electrocardiogram (the flat horizontal segments) is measured as the portion of the tracing following the T wave and preceding the next P wave and the segment between the P wave and the following QRS complex (PR segment). In a normal healthy heart, the baseline is equivalent to the isoelectric line (0 mV) and represents the periods in the cardiac cycle when there are no currents towards either the positive or negative ends of the ECG leads. However, in a diseased heart, the baseline may be depressed (e.g., cardiac ischemia) or elevated (e.g., myocardial infarction) relative to the isoelectric line due to injury currents during the TP and PR intervals when the ventricles are at rest. The ST segment typically remains close to the isoelectric line as this is the period when the ventricles are fully depolarized and thus no currents can be in the ECG leads. Since most ECG recordings do not indicate where the 0 mV line is, baseline depression often gives the appearance of an elevation of the ST segment and conversely baseline elevation gives the appearance of depression of the ST segment.

Table 1 Morphological parameters of ECG signal

Feature	Description	Duration
RR interval	The interval between an R wave and the next R wave; normal resting heart rate is between 60 and 100bpm.	0.6 to 1.2 s
QRS complex	The QRS complex reflects the rapid depolarization of the right and left ventricles. The ventricles have a large muscle mass compared to the atria, so the QRS complex usually has a much larger amplitude than the P-wave.	80 to 120 ms
ST segment	The ST segment connects the QRS complex and the T wave. The ST segment represents the period when the ventricles are depolarized. It is electric.	80 to 120 ms
T wave	The T wave represents the repolarization (or recovery) of the ventricles. 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 (or vulnerable period).	160 ms
ST interval	The ST interval is measured from the J point to the end of the T wave.	320 ms
QT interval	The QT interval is measured from the beginning of the QRS complex to the end of the T wave. A prolonged QT interval is a risk factor for ventricular tachyarrhythmias and sudden death. It varies with heart rate and, for clinical relevance, requires a correction for this, giving the QTc.	Up to 420 ms in heart rate of 60 bpm

III. INTERVALS AND SEGMENTS

PR Interval : From the start of the P wave to the start of the QRS complex

PR Segment : From the end of the P wave to the start of the QRS complex

J Point : The junction between the QRS complex and the ST segment

QT Interval : From the start of the QRS complex to the end of the T wave

QRS Interval : From the start to the end of the QRS complex

ST Segment : From the end of the QRS complex (J point) to the start of the T wave

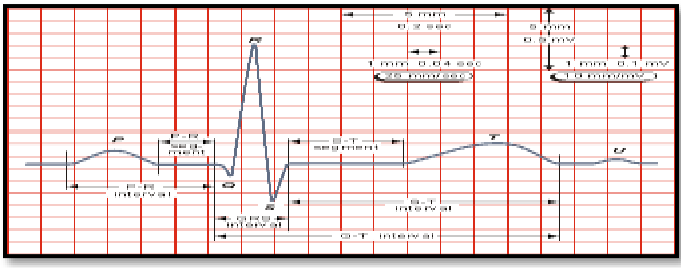

Fig. 1 Intervals and Segments in ECG signal

IV. ARRHYTHMIA ANALYSIS

An irregular heartbeat is an arrhythmia (also called dysrhythmia). Heart rates can also be irregular. A normal heart rate is 50 to 100 beats per minute. Arrhythmias and abnormal heart rates don't necessarily occur together. Arrhythmias can occur with a normal heart rate, or with heart rates that are slow (called bradyarrhythmias less than 50 beats per minute). Arrhythmias can also occur with rapid heart rates (called tachyarrhythmia faster than 100 beats per minute). In the United States, more than 850,000 people are hospitalized for an arrhythmia each year.

Arrhythmias may be caused by many different factors, including

- Coronary artery disease.
- Electrolyte imbalances in your blood (such as sodium or potassium).
- Changes in your heart muscle.
- Injury from a heart attack.
- Healing process after heart surgery.
- Irregular heart rhythms can also occur in "normal, healthy" hearts.

V. ECG RHYTHMS

This section is intended to give you an insight into some of the ECG's you may come across while working in the pre hospital environment. (Note these are rhythm strips and not diagnostic 12 lead patterns)

A. Normal Sinus Rhythm

Fig. 2 Normal Sinus Rhythm

Looking at the ECG you'll see that:

- Rhythm - Regular
- Rate - (60-99 bpm)
- QRS Duration - Normal
- P Wave - Visible before each QRS complex
- P-R Interval - Normal

B. Sinus Bradycardia

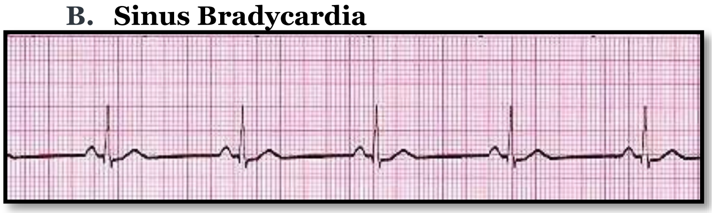

Fig. 3 Sinus Bradycardia

A heart rate less than 60 beats per minute (BPM). This in a healthy athletic person may be 'normal', but other causes may be due to increased vagal tone from drug abuse, hypoglycemia and brain injury with increase intracranial pressure (ICP) as examples

Looking at the ECG you'll see that:

- Rhythm - Regular
- Rate - less than 60 beats per minute
- QRS Duration - Normal
- P Wave - Visible before each QRS complex
- P-R Interval – Normal

C. Sinus Tachycardia

Fig. 4 Sinus Tachycardia

An excessive heart rate above 100 beats per minute (BPM) which originates from the SA node. Causes include stress, fright, illness and exercise. Not usually a surprise if it is triggered in response to regulatory changes e.g. shock. But if there is no apparent trigger then medications may be required to suppress the rhythm

Looking at the ECG you'll see that:

- Rhythm - Regular
- Rate - More than 100 beats per minute
- QRS Duration - Normal
- P Wave - Visible before each QRS complex
- P-R Interval – Normal

The impulse generating the heart beats are normal, but they are occurring at a faster pace than normal. Seen during exercise.

VI. WAVELETS

Wavelets are a powerful tool for the representation and analysis of such physiologic waveforms because a wavelet has finite duration (compact support) as contrasted with Fourier methods based on sinusoids of infinite duration. The Fourier transform is a tool widely used for many scientific purposes, but it is well suited only to the study of stationary signals where all frequencies have an infinite coherence time. The Fourier analysis brings only global information which is not sufficient to detect compact patterns. Gabor introduced a local Fourier analysis, taking into account a sliding window, leading to a time frequency analysis. This method is only applicable to situations where the coherence time is independent of the frequency. This is the case for instance for singing signals which have their coherence time determined by the geometry of the oral cavity. Morlet introduced the Wavelet Transform in order to have a coherence time proportional to the period. The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions. Because of this collection of representations we can speak of a multi resolution analysis. In the case of wavelets we normally do not speak about time-frequency representations but about time-scale representations, scale being in a way the opposite of frequency, because the term frequency is reserved for the Fourier transform.

The wavelet transform describes a multi-resolution decomposition process in terms of expansion of a signal onto a set of wavelet basis functions. Discrete Wavelet Transformation has its own excellent space frequency localization property. Application of DWT in 1D signal corresponds to 1D filter in each dimension. The input Daubechies Wavelet as mother wavelet is divided into 8 non-overlapping multi-resolution sub-bands by the filters, namely db1, db2, db3 up to db8, where db is acronym for Daubechies. The sub-band is processed further to obtain the next coarser scale of wavelet coefficients, until some final scale "N" is reached. When a signal is decomposed into 8 levels, the db6 sub-band signal best reflects the original signal, since according to the wavelet theory, the approximation signal at level n is the aggregation of the approximation at level n-1 plus the detail at level n-1.

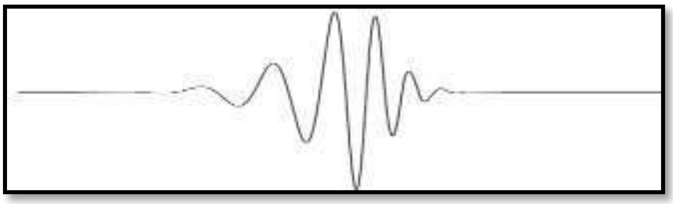

Fig. 5 Daubechis Wavelet

The large number of known wavelet families and functions provides a rich space in which to search for a wavelet which will very efficiently represent a signal of interest in a large variety of applications. Wavelet families include Biorthogonal, Coif let, Haar, Symmlet, Daubechis wavelets, etc. There is no absolute way to choose a certain wavelet. The choice of the wavelet function depends on the application.

VII. BAYES CLASSIFIER

The naive Bayes classifier is easy to build with no complicated, which makes it particularly useful for hardware implementation. It assumes naive and strong independent distributions between the feature vectors, and this assumption was met, since all the extracted ECG features were independently analyzed and assessed from the beginning. The architecture of the classifier is implemented, as shown in Fig.6

The Bayesian classifier uses Bayes theorem to find out the probability of a data belonging to a particular class given observations. For a set of feature vectors d and class ci, the Bayes theorem is given in

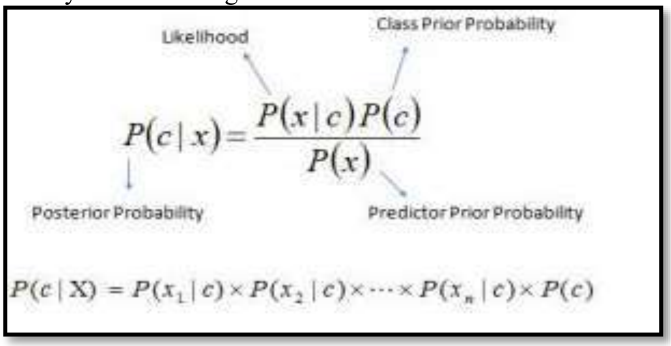

Fig. 6 An Bayes classifier

The best class to assign data is the one that maximizes this conditional probability out of all the classes. This can be represented by the following:

c = argmax P (ci | d)

c = argmax P (ci) P (x | ci)

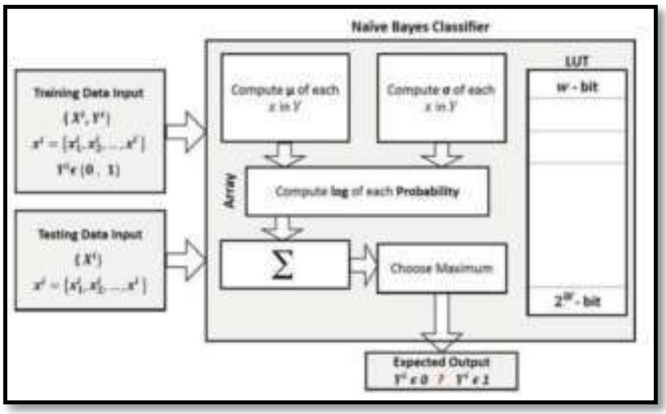

Fig. 7 Architecture of naive Bayes classifier

Fig. 7 shows the operation of the classifier, that the training and testing data features are entered in classifier. The naïve bayes classifier stores the features of arrhythmia signal and the normal ECG waveform signal. If the signal pass through the classifier is abnormal the classifier compares the signal with existing signal features and gives the result. Here normal ECG signal is given to the classifier so there is no any detection in the waveform. By this process we can easily predict arrhythmia signal before it come.

The log of the probabilities is calculated using a lookup table (LUT) whose entries are w-bit wide and 2w -bit deep (w = 8 bit). The entries in the LUT are represented in two's complement format. For any unclassified new value, we build the Gaussian model by computing the above equations from the training data set for each class. In our case, we have two classes only, GROUP A and GROUP B, which simplifies the process even more. The training data are stored in an off-chip memory because of its size. The pseudocode of both the training and testing algorithms.

VIII. CLASSIFICATION PROCESS

The first stage of ECG signal processing is preprocessing, where it is necessary to eliminate noises from input signals using Wavelet Transform. For pre-processing of the ECG signal, noise elimination involves different strategies for various noise sources. This pre- process of ECG signal is done before the extracting the feature, can result better extracted features to increase the system efficiency. Preprocessing of ECG signal consists of De-noising of ECG signal and baseline wander removal using multi resolution wavelet transform.

The noise artifacts that generally affect ECG signals is Baseline wandering. Normally it appears from respiration and lies between 0.15 and 0.3 Hz. Elimination of baseline wander is therefore needed in the ECG signal analysis to diminish the irregularities in beat morphology. In this project, the baseline wander of ECG waveform is eliminated by first loading the original signal then smooth's the data in the column vector y using a moving average filter. Results are obtained in the column vector y. We have selected span for our work for smoothing the data is 150 for smoothing it and finally subtracted the smoothed signal from the original signal. Hence, this computed signal is free from baseline drift.

In this stage the different noise structures are eliminated using Daubechis wavelet of order four. De-noising Procedure of the Signal consists of three important steps.The signal details are influenced by high frequencies at the first level, whereas the low frequencies influence the approximations of one dimension discrete signals. Wavelet Transform method for de-noising of the ECG signal decomposes the signal into different components that materialize at different scales. In the first step, the appropriate wavelet function is selected and decomposed the signal at level N. next step is to select the Threshold using various techniques, in this project the automatic thresholding techniques is employed. De-noising of ECG signal is performed by wden() function provided by wavelet toolbox.

Online implementation of state machine logic is performed to determine Peaks and location of various ECG signal parameters such as peaks and locations of R, S and T wave and p and Q waves are determined using offline technique. further RR interval, ST segment, PR interval and TT interval etc are calculated using the basic logic to find distance between occurrence of the required parameter.

After the noise elimination, baseline wanders removal and peak detection it is necessary to extract the feature of the ECG waveform in order to use it in the next stage of ECG signal analysis. The ability to manipulate and compute the data in compressed parameters form is one of the most important application of wavelet transform, are often known as features. Feature extraction is the most important step in pattern recognition. There are several ways to extract the feature of ECG signal.

CONCLUSION

The abnormality detection of the ECG signal based on discrete wavelet transform and bayes classifier is 90% efficient. The 24 randomly selected records of one minute recording are considered to classify the ECG signal. The classification of MIT-BIH arrhythmia database records into normal and abnormal classes is performed based on morphological and wavelet parameters of ECG signal.

REFERENCES

1. *Li, C. Zheng, C. Tai, Detection of ECG characteristic points by wavelet transforms, IEEE Transactions on Biomedical Engineering 42(1), (1995) 21–28.*
2. *Saurabh Pal, Madhuchhanda Mitra, Detection of ECG characteristic points using Multiresolution WaveletAnalysis based Selective Coefficient Method, Elsevier, Measurement 43 (2010), 255–261.*
3. *S. Karpagachelvi, Dr. M.Arthanari, Prof. & Head, M. Sivakumar, QRS Wave Detection Using Multiresolution Analysis, Vol. 10 Issue 5 Ver. 1.0, (2010), 39-42.*
4. *Cuiwei Li, Chongxun Zheng, and Changfeng Tai, "Detection of ECG Characteristic points using Wavelet Transforms", IEEE Trans. Biomed.Eng, Vol. 42, No. 1, (1995).*
5. *V. Vijaya, K. Kishan Rao, V. Rama, "Arrhythmia Detection through ECG Feature Extraction using Wavelet Analysis", European Journal of Scientific Research, Vol. 66, pp. 441-448, 2011.*
6. *M. Kania, M. Fereniec, R. Maniewski, "Wavelet Denoising for Multi-lead High Resolution ECG Signals", Measurement Science Review, Vol. 7, Section 2, No. 4, 2007 "ECG Learning Center", Dr. Frank G. Yanowitz, M.D., University of Utah School of Medicine http://medlib.med.utah.edu/kw/e*