

ABSTRACT

The electrocardiogram (ECG) is the recording of the electrical potential of heart versus time. The analysis of ECG signal has great importance in the detection of cardiac abnormalities. The electrocardiographic signals are often contaminated by noise from diverse sources. Noises that commonly disturb the basic electrocardiogram are power line interference, instrumentation noise, external electromagnetic field interference, noise due to random body movements and respirational movements. These noises can be classified according to their frequency content. It is essential to reduce these disturbances in ECG signal to improve accuracy and reliability.

Proposed research works offers ECG signal classification system uses Principal Component Analysis (PCA) technique to reduce the dimensionality of test signal. Discrete Wavelet Transform is used for feature extraction. Spectral flatness is another feature for the spectrum of ECG. This process helps in enhancing the classification accuracy. Classification is done using Neural Network classifier.

KEYWORDS: ECG, Wavelet Coefficients, PVC, DWT, HRV.

INTRODUCTION

In the most recent ten years, gigantic piece of the research has been centred around the transforming of biomedical signals. Every day clinical practice creates any measure of biomedical signals amid checking of patients and for indicative purposes. Accordingly automatic processing frameworks are often utilized as a part of medical data investigation. New techniques can streamline and accelerate the handling of huge volumes of information. The doctor regularly needs to choose a patient's diagnosis on the premise of various numerical qualities measured amid examination. Introduction in this volume of information is not generally simple and unambiguous. Subsequently there exist consultation frameworks that help and minimize human errors.

Electrocardiogram (ECG) is the record of the electrical potentials produced by the heart. The electrical wave is generated by depolarization and repolarization of certain cells due to movement of Na⁺ and K⁺ ions in the blood. The ECG signal is typically in the range of 2 mV and requires a recording bandwidth of 0.1 to 120 Hz [1]. The ECG is acquired by a non-invasive technique, i.e. placing electrodes at standardized locations on the skin of the patient [2]. The ECG signal and heart rate reflects the cardiac health of human heart. Any disorder in heart rate or rhythm or change in the morphological pattern of ECG signal is an indication of cardiac arrhythmia. It is detected and diagnosed by analysis of the recorded ECG waveform. The amplitude and duration of the P-QRS-T-U wave contains useful information about the nature of disease related to heart.

An Electrocardiogram or ECG is an electrical recording of the heart and is used in the investigation of heart disease. This ECG can be classified as normal and abnormal signals. One of the most important problems in ECG analysis is automatic beat delineation. This is needed in many cases ranging from simple heart rate computations to serving as the first stage of complex automatic diagnosis. Beat delineation techniques have to start by identifying features in the ECG signal that can constantly be detected in each heartbeat. Simply by looking at an ECG plot, it can be noticed that the QRS complex is the predominant feature in every beat. The other features of the ECG signal, like the P wave and T wave, are sometimes too small to be detected [3]. This makes the QRS complex the feature that can yield the best detection accuracy. The ECG is a bioelectric signal, which records the

electrical activity of heart versus time. Therefore, it is an important diagnostic tool for assessing heart function [4]. The ECG is acquired by placing electrodes on the skin of the patient [5]

Table 1 shows different features of ECG along with the intervals and amplitudes.

Features	Description	Amplitude	Duration
P wave	Atrial depolarization	0.1-0.2 mv	80 ms
PR interval	Reflects the time the electrical impulse takes to travel from the sinus node through the AV node and entering the ventricles	–	120-200ms
QRS complex	Depolarization of ventricles	1-1.2 mv	80-120 ms
J point	Point where QRS complex is finished	–	–
ST interval	Represents the period when the ventricles are depolarized	80-120 ms	ST interval
T wave	Repolarisation of ventricles	0.12-0.3mv	160 ms
QT interval	It 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	–	300-430ms
U wave	repolarisation of the papillary muscles, rarely seen	–	–
RR interval	The interval between an R wave and the next R wave	–	0.2-1.2 s

PROPOSED METHODOLOGY

The first stage is pre-processing stage including five levels of data processing which are signal filtering, QRS feature extraction, dimensionality reduction using principal component analysis (PCA), discrete wavelet transform (DWT) and independent component features extraction using spectral flatness and trained by using Neural Network classifier to classify LBBB, NSR, AFIB, RBBB, SBR, AFL, PVC and BII features of ECG signal. The ECG signal downloaded from MIT-BIH database may contain artefacts, noise and baseline wanders. Therefore it is necessary to denoise the ECG signal to remove all these unwanted parts of the signal. After denoising the ECG, it is subjected to QRS complex detection using Pan Tompkins algorithm. The QRS complex is physiologically an important peak in the ECG signal, also it is easy to detect by signal processing algorithms due to its sharp and prominent shape. In this research work, we have used Pan Tompkins algorithm for detection of QRS complex [6]. The algorithm consists of computation of derivatives, moving window integrator, squaring and detection of rising edge of pulses. The derivative provides the slope information of ECG waveform, squaring will emphasize higher amplitudes and suppresses smaller amplitudes and moving window integrator performs averaging operation, thereby removes noise.

After detection of QRS complex, 90 samples were chosen from the left side of QRS mid-point and 90 samples after QRS mid-point. We can use the entire 180 samples for training but this may give rise to two problems namely overtraining and excessive computational overhead. Overtraining affects the accuracy adversely while computational overhead will put constraints on the speed and required resources. Hence only useful features have to be identified so that only these features can be used for training and avoid the above mentioned problems. The methodology consists of following subsections.

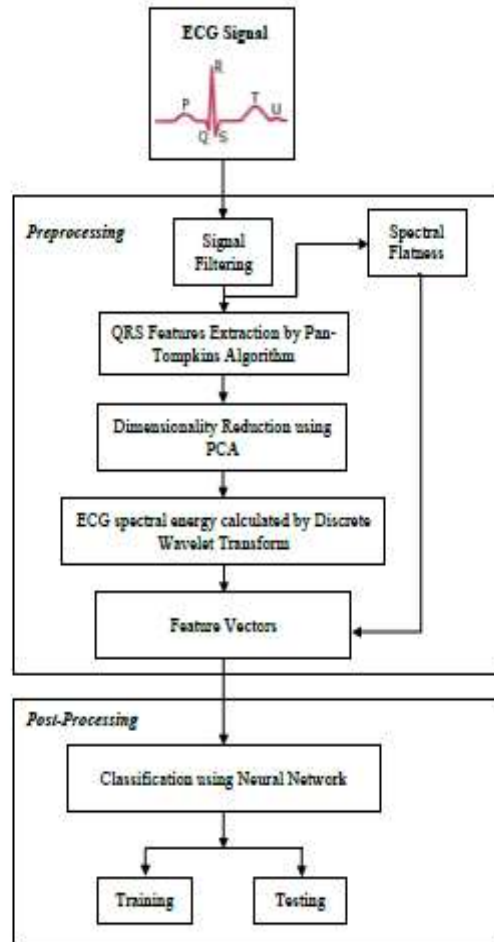


Figure 1: Flow diagram of proposed research work

SIMULATION RESULTS

An initial set of beat labels was produced by a simple slope-sensitive QRS detector, which marked each detected event as a normal beat. Two identical 150-foot chart recordings were printed for each 30-minute record, with these initial beat labels in the margin. For each record, the two charts were given to two cardiologists, who worked on them independently. The cardiologists added additional beat labels where the detector missed beats, deleted false detections as necessary, and changed the labels for all abnormal beats. They also added rhythm labels, signal quality labels, and comments.

Simulation is carried out using MATLAB2010a.

Confusion Matrix

Output Class	1	2	3	4	5	6	7	8	
1	19 11.9%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
2	1 0.6%	20 12.5%	0 0.0%	0 0.0%	0 0.0%	1 0.6%	0 0.0%	0 0.0%	90.9% 9.1%
3	0 0.0%	0 0.0%	20 12.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
4	0 0.0%	0 0.0%	0 0.0%	20 12.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	20 12.5%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	19 11.9%	0 0.0%	0 0.0%	100% 0.0%
7	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	18 11.3%	0 0.0%	100% 0.0%
8	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	2 1.3%	20 12.5%	90.9% 9.1%
	95.0% 5.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	95.0% 5.0%	90.0% 10.0%	100% 0.0%	97.5% 2.5%
	1	2	3	4	5	6	7	8	

Target Class

Figure 2: Confusion Matrix plot for proposed scheme

CONCLUSION

Automatic detection of heart arrhythmias could be very important in clinical usage and lead to early detection of a fairly common malady and could help contribute to reduced mortality. In this research work, the use of Neural Networks for classification of the ECG beats is presented. Several stages of pre-processing have been used in order to prepare the most appropriate input vector for the neural classifier.

It was found that the accuracy of proposed algorithm is nearly around:

97.5 % for NN using db5

It was found that the sensitivity of proposed algorithm is nearly around:

95% for NN using db5

The data is compared with MIT-BIH database. It is clear that the proposed Neural Network classifier based scheme gives higher accuracy with Haar wavelet as compared to previous research work (96.33%) done by Kelwade and Salankar 2016 in .

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