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Classification of Myocardial Infarction Using Multi Resolution Wavelet Analysis of ECG

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Abstract

In this paper, classification of anterior and inferior myocardial infarction from normal cases is done using the changes happening in ECG waves. Depth of Q peak and elevation in ST segment is taken in consideration for classification purpose. A multiresolution approach along with an adaptive thresholding is used to extract these ECG features. Classification of inferior myocardial infarction (IMI) and anterior myocardial infarction (AMI) is done using a simple adaptive threshold (SAT) method. The sensitivity, specificity and accuracy is 93.22%, 94.28% and 93.61% respectively in case of IMI and in AMI cases its 83.33%, 88.57%, 86.15% respectively. Classification is also done using artificial neural network, but its performance is comparatively low. This may be due to inadequacy of data available. The PTB diagnostic ECG database is used for evaluation of the methods.

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Keywords: Anterior myocardial infarction; Artificial neural network; Inferior myocardial infarction; Simple adaptive threshold method.

1. Introduction

Electric depolarization and re-polarization of the human heart happens due to the disturbance in ion concentration of cardiac cells. Superimposition of this depolarization and re-polarization produces ionic signals, which is converted into ECG (Electrocardiogram) using Electrocardiograph. One cardiac cycle of a normal ECG signal consists of P-QRS-T waves as shown in Fig 1. Any change in the rhythm or cardiac cycles of an ECG signal may indicate some heart diseases. First application of computer in medicine was perhaps the computerized automatic cardiac diagnosis

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[1]. Now it's an established area of research in the field of biomedical engineering. QRS complex in an ECG signal, plays an important role in determining heart rate and extracting cardiac cycles of an ECG signal. Many algorithms have been developed for detection of QRS complex [2-4]. Usually an ECG signal is corrupted by some external and physiological noises. It happens due to power line interference, respiration, motion artifacts, muscle contraction and noise produced by electro-surgical equipments [5]. These noises can be removed by discarding certain noisy frequency bands through DWT decomposition of the signal [4].Since ECG is a non-stationary signal, wavelet transform is required to analyse ECG signals [6].

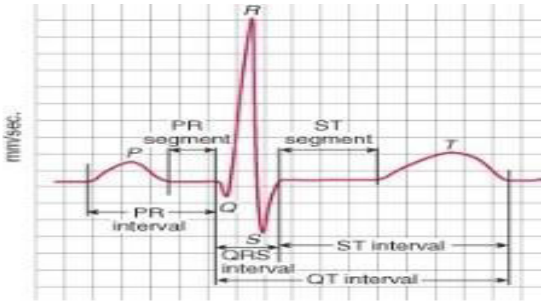

Fig. 1. ECG beat with marked characteristics points

The classification of ECG signals is a challenging problem because ECG signals may show significant variations for different patients. Classification of myocardial infarction cases are addressed in [7-8]. But these classifications only detects myocardial infarction cases generally. There are seven types of myocardial infarction, and different MI indicates destruction of heart tissues at different locations of human heart. If detection of the type of myocardial infarction can be done then one can identify the location and severity of myocardial infarction. Cross wavelet transform can be used to detect inferior myocardial infarction [9].

Using proposed method in this paper, inferior and anterior myocardial infarction can be detected with high accuracy. AMI carries the worst prognosis of all infarct locations, mostly due to larger infarct size. IMI account 40-50% more prominent of all acute myocardial infarctions. Nearly 50% of patients suffering from inferior infarction will have complications associated with mortality [10]. AMI involve anterior part and ventricular septum of the heart and in case of IMI, inferior wall of the heart is get affected. In the standard 12 lead ECG, abnormal changes in the inferior leads: ii, iii and avf shows the presence of inferior myocardial infarction and variation in leads V2, V3 and V5 indicates the presence of anterior myocardial infarction[11-13].

2. Proposed Method

ECG features can be used for classification of myocardial infarction. ST segment elevation and deep Q peak is usually seen in case of a patient suffering from myocardial infarction. But these changes do not happens simultaneously in a clinical practice. At first, ST segment is elevated. After 1 week, Q wave will start deepening and ST segment will start returning to normal. In third week deep Q wave will become fully developed. By the end of 3 months, ST segment will completely return to normal, but Q wave will remain deep permanently. So after obtaining Q peak depth and ST segment elevation, classification is done. The samples are classified using a simple adaptive threshold method and artificial neural network. In this paper, classification of inferior, anterior myocardial infarction and healthy ones is done. In case of inferior myocardial infarction, these changes are prominent in leads ii, iii and avf. For anterior myocardial infarction, these changes are seen in leads V2, V3 and V5.

2.1. ECG Feature Extraction

The steps followed in ECG feature extraction is shown in the block diagram in Fig 2. At first an ECG signal of 1 kHz of sampling frequency is applied to DWT decomposition up to level 9 as shown in Fig 3. This DWT decomposition is used to extract certain frequency components that will help in denoisng and QRS band detection.

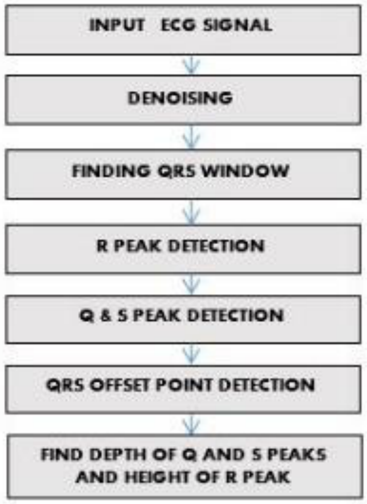

Fig. 2. ECG feature extraction

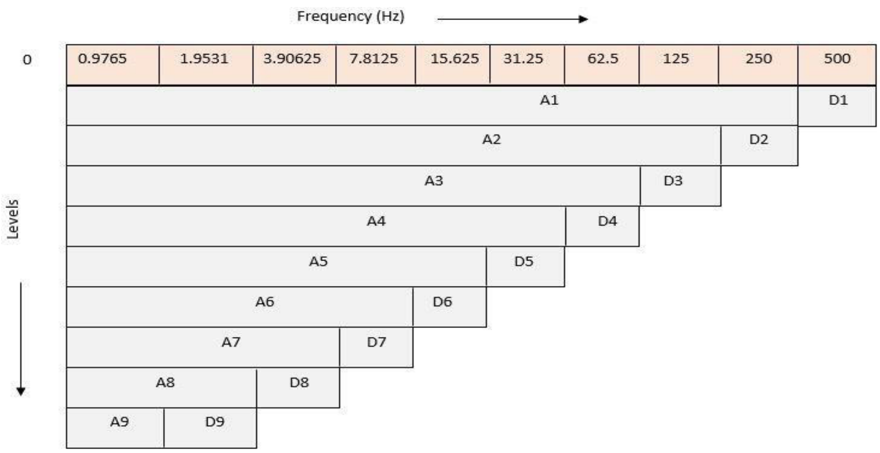

Fig. 3. DWT decomposition structure.

The noise frequency bands are identified and their elimination is carried out in two basic steps: (A) high frequency noise removal (B) baseline wander correction and power line interference removal.

The bandwidth of an ECG usually ranges between 0-100 Hz. So in order to remove all high frequency noises, the detail coefficients D1 and D2 are discarded. The frequency of new ECG signal obtained after removal of these noises ranges from 0 to 125 Hz.

In ECG signal drift from baseline happens due to respiration. Frequency of respiration gets added to the ECG during its acquisition. The baseline variation frequency is 0.15-0.8 Hz [4]. Motion artifacts are transient baseline changes caused by change in the electrode skin impedance with electrode motion. The baseline disturbances caused by motion artefact can be assumed as a signal resembling one cycle of a sine wave and is within the frequency range of baseline drift. Discarding A9 frequency band and reconstructing the signal eliminates these two noises. In case of ECG analysis through ptb-db database for classification of different types of myocardial infarction, power line frequency is 60 Hz. This component is rejected using a notch filter.

To find QRS windows in an ECG signal, denoised ECG signal is again decomposed up to level 9. QRS complex regions are more prominent in details at scale D5 and D6. So an array QRS-DET is formed by addition of detail components D5 and D6. In order to find the QRS complexes from QRS-DET, an adaptive threshold value is set which is equal to the n times of the mean amplitude value of QRS-DET array. Typical value of n used in this paper is 3. Since the maximum width of the QRS complex for any patient is not more than 160 milliseconds, a fixed window of same width is searched in QRS-DET to detect the indices, where the threshold condition is satisfied. Between two consecutive searches, a blanking period of 200 milliseconds is offered.

R peaks can be obtained by searching the maximum amplitude data point within each QRS window. Position of corresponding data points in a denoised signal are stored as a vector. This vector will help to obtain Q and S peaks. To find Q and S indices, set windows: R index-80 to R index for finding Q index and R index to R index+80 for finding S index. In those windows data points having minimum amplitude values are searched, to obtain Q and S peaks. Then QRS offset windows: S index to S index+40 is used to find QRS offset index. Then search for positions corresponding to minimum slopes in those windows.

As shown in Fig 4, T peak of a cardiac cycle will lie in two third of an R-R interval and in rest of the one third of R-R interval, peak P of next cardiac cycle will exist [4]. The interval between two adjacent R peaks is divided in a ratio of 2:1, which is demarcated by TP index. Since this TP index lie along with the baseline of ECG, it's taken as reference to extract heights and depth of peaks in ECG as follows:

- Q peak depth = Amplitude of ECG at Q peak - Amplitude of ECG at TP index.
- S peak depth = Amplitude of ECG at S peak - Amplitude of ECG at TP index.
- R peak height = Amplitude of ECG at R peak - Amplitude of ECG at TP index.

2.2. Detection of Elevation in ST Segment

For detection of ST segment, at first ST segment duration must be detected. For a cardiac cycle, the ST segment lies in interval from QRS offset index to QRS offset index +90 in myocardial infarction cases. The data point with maximum amplitude in an ST segment is marked as an ST peak data point. Elevation in ST segment = Amplitude of ECG at ST peak - Amplitude of ECG at TP index.

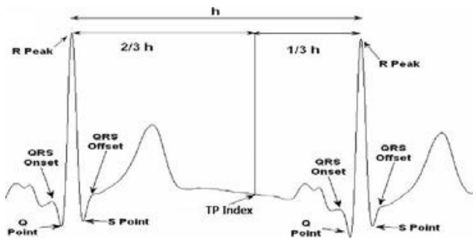

Fig. 4. Region ratio between T offset of current beat and P onset of next beat.

2.3. Classification Methodology

2.3.1. *SAT method:* This method is separately used for both IMI and AMI case classification. For IMI classification, deep Q peak or elevated ST segment is usually seen in lead ii, iii and avf. So ECG corresponding to these leads are taken for ECG feature extraction and classification. Here ECG of 59 IMI cases and 35 normal cases are taken for classification, from ptb-db database. Mean of depth of Q peak and elevation in ST segment of lead ii, iii and avf are named as t-q-ii, t-st-ii,t-q-iii, t-st-ii,t-q-avf and t-st-avf respectively are taken as threshold. If any ECG signal of lead ii is having Q peak depth less than t-q-ii or elevation in ST segment greater than t-st-ii, then it's marked as IMI case. Similar rule is applied for lead iii and avf.

For AMI classification deep Q peak usually seen in lead V3 or elevated ST segment is seen in lead V2 and V5. In this case from ptb-db database, ECG of 30 AMI cases and 35 normal cases are taken for classification. Here also mean of depth of Q peak and elevation in ST segment is taken as threshold. Corresponding to lead ii, iii and avf they are named as t-q-V3, t-st-V2 and t-st-V5 respectively. If any ECG signal of lead V3 is having q peak depth less than t-q-V3 or if elevation in ST segment in lead V2 is greater than t-st-V2 then it's marked as AMI case. Similarly if elevation in ST segment in lead V5 is greater than t-st-V2 then also it's marked as AMI case.

2.3.2. *Artificial neural network method:* In this paper, a feed-forward back propagation network is created with five layers: one input layer, one output layer and three hidden layers. First, second and third hidden layers consists of 10, 5 and 2 nodes respectively. Here log sigmoid function is used as activation function and feed forward networks have one-way connections from input to output layers.

The network training function used is traincgb, in order to update weight and bias values according to the conjugate gradient back propagation. To train ANN classifier, normalized feature vectors as well as the labelled output vector were given for each frame. To classify IMI cases and normal cases, 45 IMI and 25 normal cases detected correctly in SAT method, total 70 cases are taken as input for training, each with 6 features as shown in Fig 5., and remaining 24 cases are tested. To classify AMI cases and normal cases, 20 AMI and 20 normal cases detected correctly, total 40 cases were taken as input for training, each with 3 features as shown in Fig 6, and remaining 25 cases are tested.

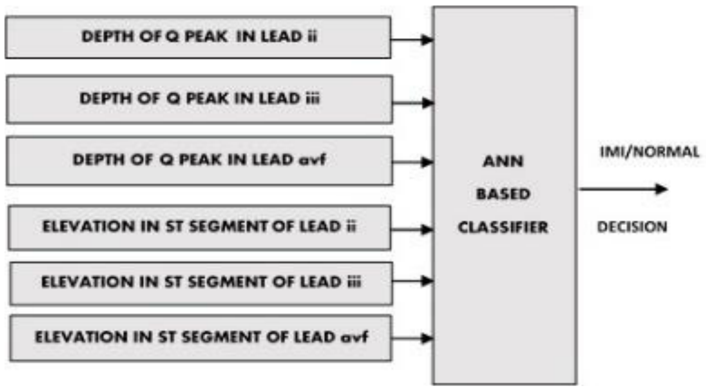

Fig. 5. Block schematic of IMI/normal classifier

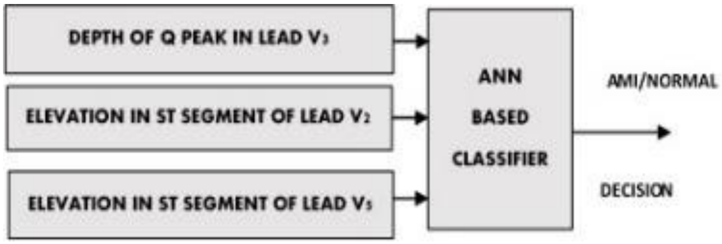

Fig. 6. Block schematic of AMI/normal classifier

3. Experimental Results

3.1. Denoised ECG Signals

The signal suffering from power line interference effect shown in Fig 7(a) can be processed into a better signal by using a notch filter as shown in Fig 7(b). The original signal suffering from drift of the baseline is caused due to respiration, which is more likely to be as a nearly sinusoidal component is shown in Fig 8(a). On correcting baseline error signal, the result obtained is shown in Fig 8(b).

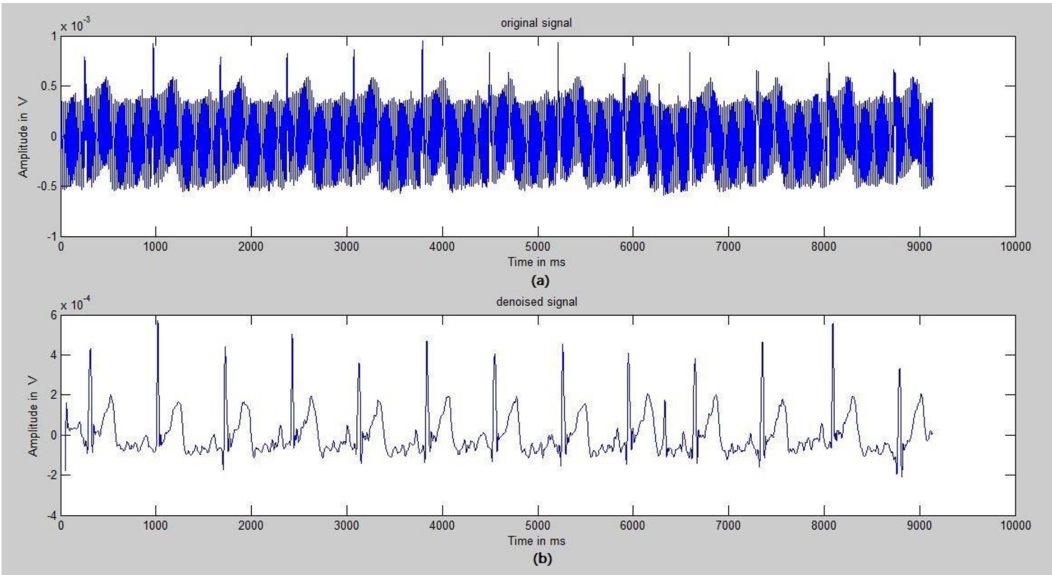

Fig. 7. (a) Original signal suffering from power line frequency effect; (b) Denoised signal obtained after removal of power line frequency effect.

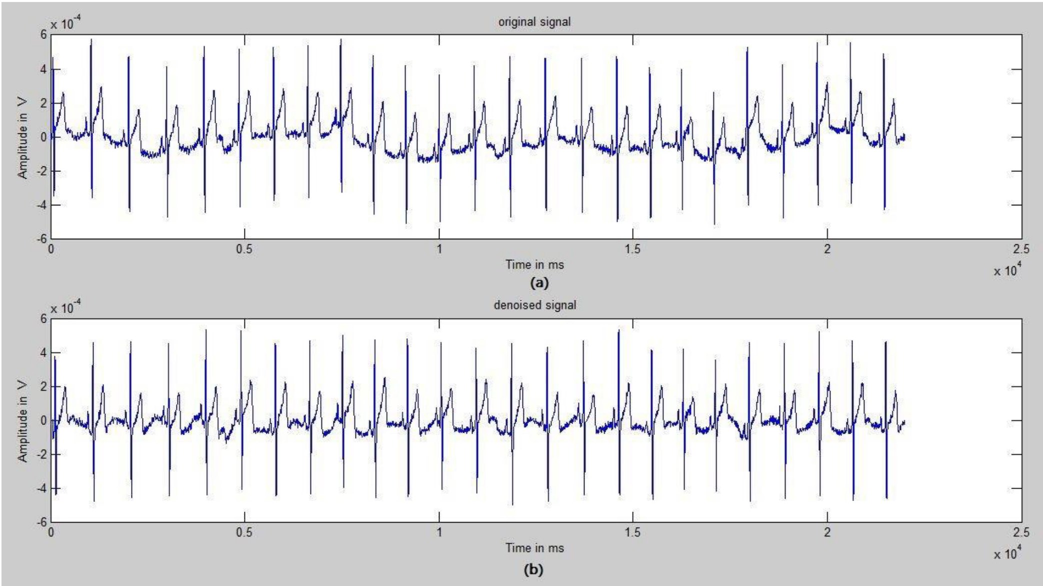

Fig. 8. (a) Original signal suffering from baseline error; (b) Denoised signal obtained after removal of baseline error.

3.2. Classification Using SAT Method

On using this method, in IMI classification process 55 IMI and 33 normal cases are detected correctly. In case of AMI classification, 25 AMI and 31 normal cases are correctly detected. Sensitivity, specificity and accuracy obtained in IMI and AMI classification on using SAT method is shown in Table 1.

Table 1. Sensitivity, specificity and accuracy obtained using SAT method

Parameters Obtained	IMI (%)	AMI (%)
Sensitivity	93.22	83.33
Specificity	94.28	88.57
Accuracy	93.61	86.15

3.2. Classification Using Artificial Neural Network

In IMI classification process out of 14 IMI cases taken for testing 12 are detected correctly and out of 10 normal testing inputs, 8 are detected correctly. During AMI classification process out of 10 AMI cases taken for testing, 7 are detected precisely and out of 15 normal testing inputs 13 are detected correctly. Sensitivity, specificity and accuracy obtained in IMI and AMI classification on using ANN is shown in Table 2.

Table 2. Sensitivity, specificity and accuracy obtained using ANN

Parameters Obtained	IMI (%)	AMI (%)
Sensitivity	85.71	70.00
Specificity	80.00	86.67
Accuracy	83.33	80.00

4. Conclusion

In this paper, at first ECG signals are denoised and then ECG feature extraction is done. After that step, Q peak depth and elevation in ST segment of IMI, AMI and normal case is detected, then classification of IMI and AMI from normal cases is done using SAT and ANN. The sensitivity, specificity and accuracy obtained in IMI case on using SAT method is 93.22%, 94.28% and 93.61% respectively and in AMI case its 83.33%, 88.57%, 86.15% respectively. On using ANN the sensitivity, specificity and accuracy obtained in IMI case is 85.71%, 80.00%, 83.33% respectively and in AMI case its 70.00%, 86.67%, 80.00% respectively. The performance of ANN method is comparatively low. This may be due to inadequacy of data available.

4. Future Scope

Change in different leads of a 12 lead ECG records may indicate various kinds of myocardial infarction. In future work similar classification process can used to classify remaining five types of myocardial infarction. Due to shortage of data, performance of the ANN method is comparatively low. If more data is available, then it may be possible to get better performance through ANN.

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