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CLASSIFICATION BUNDLE BLOCK DETECTION USING MAGNITUDE SQUARED COHERENCE

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ABSTRACT

This paper conveys a technique for the detection of Bundle Branch Block (BBB) ECG patterns using Magnitude Squared Coherence (MSC) function. The MSC function finds common frequencies between two signals and evaluate the similarity of the two signals. The ECG variation in BBB can observed through the changes in the ECG signal. MSC technique uses Welch method for calculating the PSD. For the detection of Normal and BBB beats, MSC output values are given as the input features for the LMNN classifier. Overall accuracy of LMNN classifier is 98.5 percent. The data was collected from MIT/BIH arrhythmia database.

Keywords: bundle b lock, MSC, LMNN classifier, Welch method, PSD, MIT-BIH a rrhythmia database.

1. INTRODUCTION

Electro-Cardiogram is used to access the functioning of a human heart. The diagnosis of the heart ailments by the doctors is done by following a standard rule set (changes). In this project our aim is to automate the above procedure so that it leads to correct diagnosis. The features talk about different segments of the ECG namely P, Q, R, S, T [1].

Bundle branch block is developed when there is block along the path that electrical pulses travel to make the heart to beat .A condition in which there is a delay in the in the heart lower chambers may be observed through the changes in the ECG. ECG is the cost effective tool for analysing the cardiac abnormalities. Good performance depends on the accurate detection of ECG features.

ECG morphological changes in Left Bundle Branch block (LBBB) are:

- Increased QRS complex duration (> 0.12 seconds).
- Increased Q wave amplitude
- Abnormal T wave.

ECG morphological changes in Right Bundle Branch block (RBBB) are:

- Increased QRS complex duration (> 0.12 seconds).
- RSR' format.
- T wave inversion.

The waveform changes in the different types of ECG beats was shown in the Figure-1, Figure-2, Figure-3. Early changes in ECG with Bundle Branch Block [1] are significant because urgent treatment can save the life of the patient from heart attack. Cardiac arrhythmia detection Using artificial neural networks with selected features are explained in [5], [18]. Statistical methods for feature extraction are explained in [4]. The RR interval, P wave based methods has some limitations [7]. Cross wavelet transform technique is explained in [2], [9] for the detection of IMI. The coherent function can be used for the analysis of different biomedical signals [14]. Coherence between ECG and EEG signals is estimated in [11].

Detection of Bundle Branch Block arrhythmia are explained in [19], [6] using morphological features. Morphological features of certain decease are difficult to be detected. This problem can be solved by using statistical features (Spectral Coherence). Bundle Branch Block signals are easily classified using spectral coherence coefficients.

Spectral Coherence coefficients are the simplest and best features for Bundle Branch Block classification and achieve good classification results. In this paper the use of Spectral coherence for discriminating normal and Bindle Branch Block signals are studied. Previously some researcher [13] used the MSC coefficients in several ways as parametric features rather than the original time series signal and achieved better results[13], [14].

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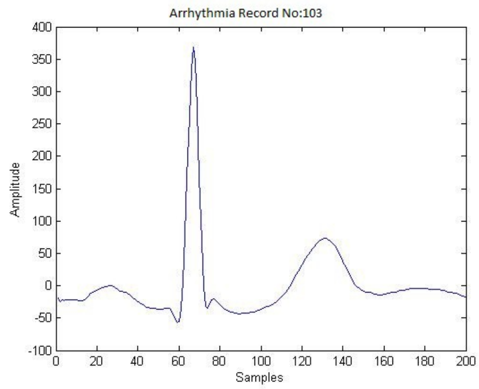

Figure-1. Normal beat.

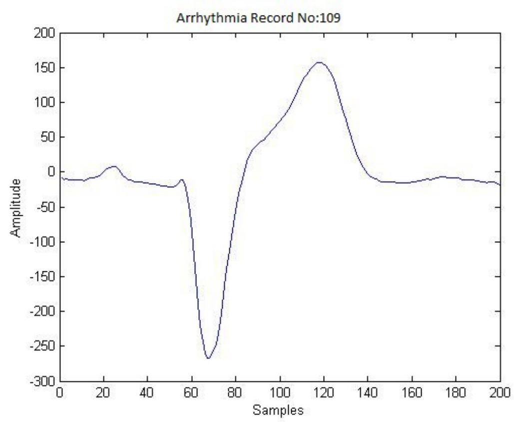

Figure-2. Left Bundle branch block.

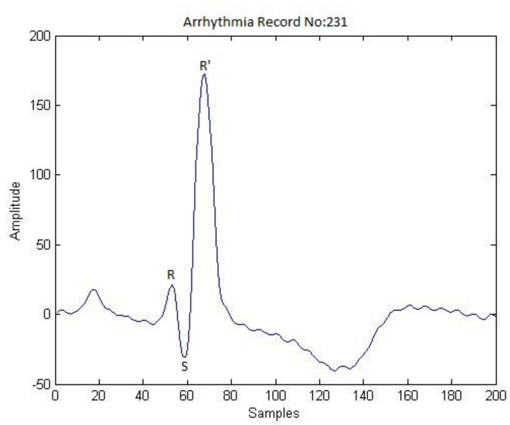

Figure-3. Right bundle branch block.

2. PRE-PROCESSING

2.1 Data

Table-1. MIH-BIH arrhythmia database.

File No.	NSR	LBBB	RBBB
100	2237	0	0
101	1858	0	0
103	2080	0	0
106	1505	0	0
109	0	2490	0
111	0	2121	0
118	0	0	2164
123	1513	0	0
124	0	0	1529
207	0	1457	85

The data for the classification was taken from the MIT BIH Arrhythmia Database [15]. Which consists of 5 normal, 3 LBBB and 3 RBBB patients data at 360Hz sampling rate of one hour duration as shown in Table-1.

2.2 Noise removal

Noise removal is a preprocessing step that removes noise present in ECG signal using filters. In the present study we have used Sgolay FIR filter for the noise removal of ECG signals.

2.3 R Peak detection

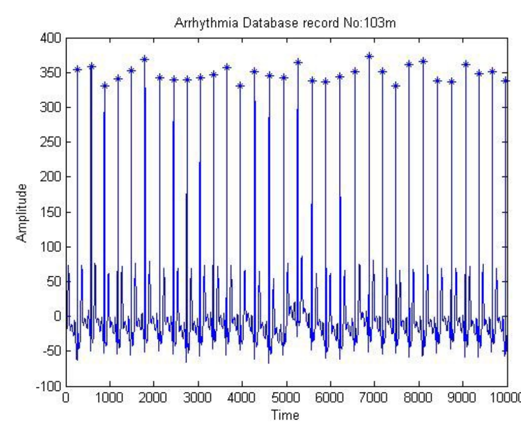

Figure-4. R peak detection.

R peaks of each ECG file are detected as shown in Figure-4. The distance between two R peaks is called

RR interval. The parameters R peak and RR interval are used to segment the ECG file into beats.

The ECG classification flow diagram is as shown in Figure-5.

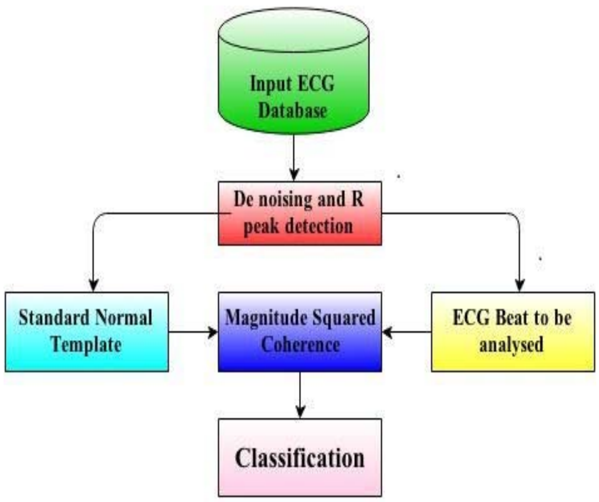

Figure-5. ECG classification flow diagram.

3. FEATURE EXTRACTION OF ECG SIGNAL

Magnitude Squared Coherence (MSC)

MSC is a standard method for analysing the level of similarity between two signals in frequency domain. Power Spectral Density (PSD) reveals the information about how energy is distributed in frequency domain. PSD can be calculated by taking FFT on the autocorrelation function [16]. The MSC function finds common frequencies between two signals and to evaluate the correlation of two signals. If the two signals are highly correlated the value of MSC is 1. where 0 MSC value indicates the two signals are uncorrelated.

MSC between the x1 and x2 can be calculated using equation 1[16].

$$C_{x1,x2}(f)=\frac{S_{x1x2}(f)}{\sqrt{S_{x1}(f)}\sqrt{S_{x2}(f)}} \tag{1}$$

$Sx1x2(f)$ is the cross PSD between x1 and x2.
$Sx1(f)$is the PSD of x1.
$Sx2(f)$ if the PSD of x2.
$0 < Cx1x2 < 1$

Table-2. MSC values for normal-normal, normal-abnormal.

MSC	N-N	N-LBBB	N-RBBB
1	0.81	0.15	0.13
2	0.91	0.37	0.52
3	0.98	0.46	0.87
4	0.98	0.53	0.50
5	0.97	0.31	0.14
6	0.89	0.02	0.52
7	0.59	0.02	0.19
8	0.58	0.15	0.32
9	0.83	0.22	0.37
10	0.86	0.23	0.40
11	0.86	0.23	0.40
12	0.86	0.23	0.40
13	0.86	0.23	0.40
14	0.86	0.23	0.40
15	0.86	0.23	0.39
16	0.87	0.22	0.41
17	0.86	0.24	0.39
AVG	0.85	0.24	0.40

3.1 Welch method for estimating PSD

In the year 1967 Welch made some modifications to the periodogram technique. They are

- Divide x1(n) in to L sub sequences.
- x1(n) is allowed to overlap.
- A window w(n) applied to each sub sequence and calculate periodogram of each sub sequence.
- Find average periodograms of all L sub sequences.

$$x1_i(n)=x1(n+iD) \tag{2}$$

$$n = 0, 1.....,L-1. \tag{3}$$

$$N = L + D(k-1) \tag{4}$$

where
L=Length of each sub sequence.
K=Total number of sub sequences

ARPN Journal of Engineering and Applied Sciences

L-D= Amount of overlapping between successive sub sequences.
N=Total length of sequence x1(n).
If D=N there is no overlap.

For calculating MSC, one ECG cardiac beat from healthy person is considered as normal template. MSC values are calculated for

- Normal template- Abnormal beat(LBBB and RBBB)
- Normal template-Normal beat

MSC value varies between 0 to 1 as shown in Table 2. For calculating MSC, the above mentioned welch method [17] is used with 30 percent overlapping with hamming window of size 32 samples. So there are 17 MSC output values (features) for the window size of 32 samples. It is observed from the results that Coherence values for Normal to Normal beat are higher than Normal template to Abnormal beat as shown in Table 2.The MSC values for normal template to all the remaining beats are calculated.

4. CLASSIFICATION OF ECG SIGNALS

4.1 Back propagation neural network

Back Propagation Neural Network (BPNN) is commonly used in the machine learning applications. BPNN structure made up of interconnected layers. The input layer, hidden layers (one or more) and output layer. The input layer is fed by the external source from outside. Hidden layer provides the internal link between input and output layers. The results of the Neural Network can be taken from the output layer.

4.1.1 Levenberg Marquart neural network

In this work for the detection of Bundle Branch Block LM back propagation Neural Network was used. This Neural Network provides rapid execution of the network to be trained, which is the main advantage in the neural signal processing applications [10].

There is no specific rule in finding the number of hidden neurons. The Back propagation neural network is basically designed to minimize the Mean squared error (MSE). Classification accuracy of NN is based on the selection of appropriate feature set, training algorithm and network design.

To test the performance of this algorithm, Scalar Conjugate Gradient (SCG) Neural Network and Levenberg Marquardt Neural Network are used. The Levenberg Marquardt algorithm is a robust and very simple method for approximating a function. The Levenberg Marquardt algorithm gives a numerical solution for minimizing a nonlinear function, over a space of parameters. The network is trained with 50 beats, and tested with 232 beats. The total number of iterations was set to 1000 and mean square error less than 0.001.

5. RESULTS

The MSC values are calculated for Normal template to all the 287 beats. These stored values (282 MSC values) of size 287x17(287 patterns each having 17 features) are given as the input features for the LM Neural Network classifier (For Training and Testing). In this work, the Bundle Branch Block is detected by the MSC technique in combination with LM Neural Network classifier. Performance of LM classifier is compared with SCG classifier. The LMNN Classifier gives better accuracy of 98.5 percent as compared to other SCG classifier as shown in Table-3.

Table-3.

Classifier	Sensitivity	Specificity	Accuracy
LM NN	96.97	98	98.5
SCG NN	86.4	100	94.07

The Coherence values for Normal template to LBBB are low in the QRS complex region as shown in Figure-6 and for Normal template to RBBB the coherence values are low in the T wave region as shown in Figure-7. For the Normal template to Normal signal the MSC values are high in all the regions of ECG signal (P, QRS, T regions) as shown in Figure-8.

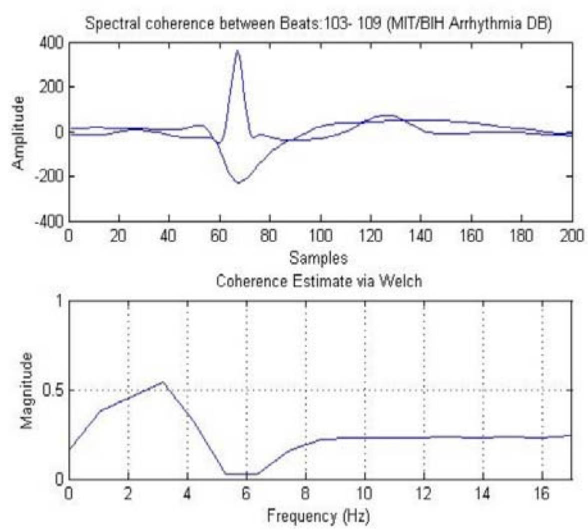

Figure-6. Spectral coherence for Normal-LBBB beats.

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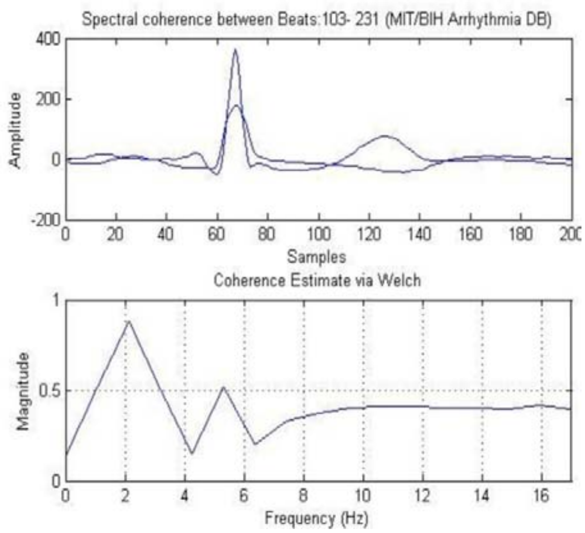

Figure-7. Spectral coherence between Normal-RBBB beats.

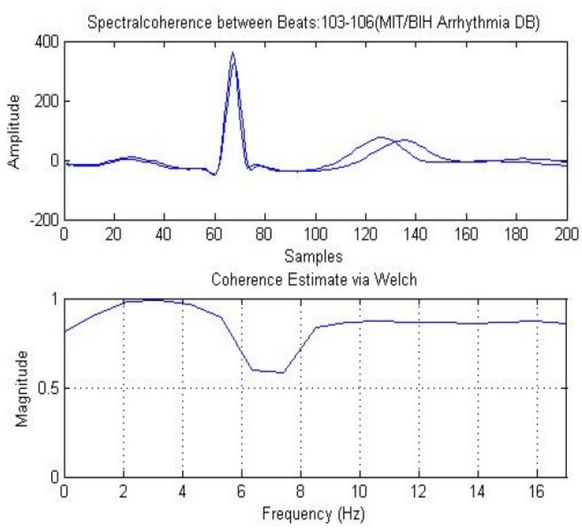

Figure-8. Spectral coherence between Normal-Normal beats.

In the Figure-9 (3D plot of Spectral Coherence) 1 to 34 values are the coherence values for Normal template to Abnormal(Mixed with LBBB and RBBB) beats showing blue colour indicating low value of MSC and from beats 35 to 119 are showing dark red colour indicating high value of coherence. Again 120 to 287 beats (mixed with LBBB and RBBB) are showing blue colour indicating low value of coherence. The network is trained with 1-50 beats, and tested with 51-287 beats. For measuring accuracy two parameters sensitivity and specificity are calculated using the following equations

$$\text{Specificity}=\frac{TN}{TN+FP}X100$$

$$\text{Sensitivity}=\frac{TP}{TP+FN}X100$$

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}X100$$

TP(True Positive) = Count of all the correctly classified Normal beats.

TN (True Negative) =Count of all beats the correctly classified Abnormal beats.

FP (False Positive) = Count of Normal beats which are classified as Abnormal.

FN (False Negative) =Count of Abnormal beats which are classified as Normal.

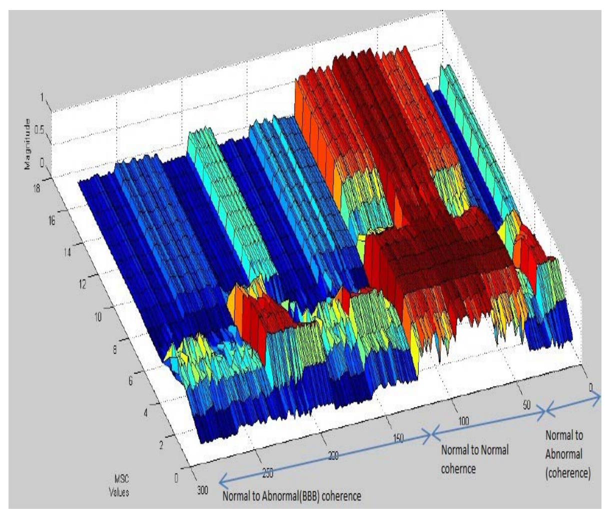

Figure-9. 3D plot of Spectral coherence values.

6. CONCLUSIONS

The Levenberg Marquardt Neural Network clearly distinguishes the Left and Right bundle blocks by taking features from the MSC technique. The Levenberg Marquardt Neural Network shows the 98.5 percent accuracy compared to Scaled conjugate decent algorithm as shown in the Table-3.

The diagnosis of a human heart is very important. It is a logical decision made by the cardiologist based on certain health indicators and changes of the ECG. If this procedure helps us to automate a certain section or part of the diagnosis then it will help the doctors and the medical community to focus on other crucial sections. This procedure has also increased the accuracy of diagnosis.

ARPN Journal of Engineering and Applied Sciences

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