Classification of Cardiac Blocks using Wavelet Delineated Cardiac Cycles

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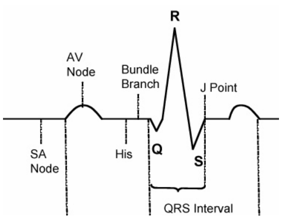
Abstract—**Classification of various types of cardiac blocks is crucial for timely detection and treatment of various cardiac conditions and abnormalities. We propose a method to increase the accuracy of classification of Atrio- Ventricular Blocks and Bundle Branch Blocks. This work is done using wavelet based cardiac cycle delineator to extract individual cardiac cycles from Electrocardiographic signals and using each of these cardiac cycles as feature vectors for a Neural network based classifier. The delineator based method is compared to a normal time domain based classification approach to check for advantages of this approach.**

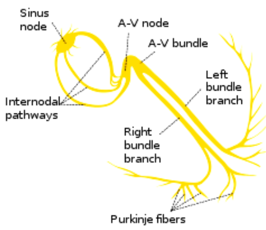
*Keywords-**AV Blocks, Bundle Branch Blocks, ECG deliniators, Wavelet transform, Neural Networks.***

I. INTRODUCTION

Electrocardiogram, also known as ECG is the most common method to monitor and keep a record of the human cardiac potentials. It maps the process of depolarization and repolarization of the heart with respect to time on a paper strip, which nowadays can be digitally recorded. The basic components of the recording are the P wave, QRS complex and T wave respectively. These basic waveforms are repeated at regular intervals of time in the same sequence giving rise to a mechanism for studying cardiac potentials. Any change from the normal cardiac cycle consisting of repeating P-QRS-T pattern signifies some kind of cardiac abnormality. The normal ECG plot for a single cardiac cycle is given in fig. 1a. The P wave represents the generation of the electrical impulse



(1a)



(1b)

Figure (1a): A complete human cardiac cycle ECG denoted by the P-QRS- T waves. The cause of generation of each of these waves is labeled in the figure itself.

Figure (1b): The human cardiac impulse generation and conduction pathway.

from the SA node and the repolarization of the atrium of the heart. The QRS complex is a combination of a series of waveforms that includes the Q wave (negative deflection after the P wave), R wave (the positive deflection after the Q wave) and the S wave (negative deflection after the R wave). The QRS complex represents the depolarization of the ventricular muscles. The T wave is the positive deflection shortly following the QRS complex; it represents the repolarization activity in the ventricles [1]. The PR interval represents the atrial depolarization and subsequent conduction through the bundle branches. The main role of the AV node is to co-ordinate the atrial and ventricular contractions by modulating the signals received from the SA node [2] [3]. The cardiac conduction pathway is shown in fig. 1b. Any abnormality in the heart is reflected through the changes in the intervals of

Figure 2: The ECG manifestation of a 2nd degree AV Block as generated on lead II of a dual channel ambulatory ECG recording.

these waves and complexes and thus, even obstructions and blocks can be detected.

Heart blocks can occur spontaneously anywhere and at anytime. There is no particular condition for predicting a heart block and this may result in serious life threatening situations. In order to have an idea about the presence of abnormalities in the heart and to treat it at the earliest, block detection is a must and due to the complications associated with it, accuracy counts a lot. We emphasize two major types of cardiac blocks in this paper, viz., the Atrio Ventricular (AV) blocks and the Bundle Branch blocks (BBB).

A. AV Blocks

AV blocks can be divided into three categories, namely, type-1 (1st degree), type-2 (2nd degree) and type-3 (3rd degree). Type-1 AV blocks are one of the most commonly seen blocks but are seldom harmful. Here, the impulse generated in the SA node is delayed in its transmission between the Atrial node and the Purkinje fibers and not actually blocked. Since, no impulse is blocked, each cycle contains the P and the QRS wave followed by the T wave, as a result of the delay, the PR interval becomes longer than the normal. Sometimes, the impulse may become so slow that the P wave hides in the preceding T wave. It is not necessary for a person to have a history of cardiac diseases to be affected by this block. It can be normal in some young and healthy adults. It is commonly found in elderly people as a manifestation of the ageing

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process. Cardiac drugs are one of the most common causes of this block. This block may change into a higher degree block if caused due to Myocardial Infarction (MI). Type-2 AV block is a true block where the impulses are actually blocked from reaching the ventricles through the defined path. The ECG manifestation of a Type- 2 AV block is given in fig. 2. Type-3 AV blocks, also called complete heart blocks are the ones in which the impulses are not at all conducted from the atria to the ventricles. When the impulse is not conducted, the ventricles start producing impulses through some auxiliary pacemakers somewhere in the ventricles but at a very slower rate causing the creation of two independent impulses. Due to the slow rate of the impulses generated in the ventricles it becomes difficult to maintain the overall functioning of the heart muscles. This block may be preceded by the other two blocks and bundle branch block. The most common cause of this block is coronary ischemia or the lack of blood flow through the coronary arteries. It is treated with the help of a dual pacemaker that generates impulses in rhythm with the impulse generated by the SA node in the atrium.

B. Bundle Branch Blocks

Bundle branch blocks occur when one or more of the bundle branches fail to conduct the electrical impulses from the AV node. This results in the altered path for ventricular depolarization. Instead of the impulse being transmitted through the normal cardiac conduction pathway, it may travel through muscle fibers. Change in the regular path leads to asynchronous ventricular activity and slows down the rate of ventricular depolarization resulting in left out or dropped cardiac output. Bundle Branch Blocks (BBB) can be classified as Right Bundle Branch Blocks (RBBB) and Left Bundle Branch Blocks (LBBB) [1].

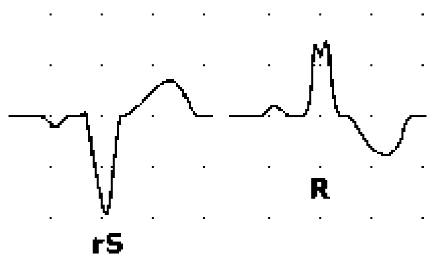

Figure 3: The ECG manifestation of LBBB as generated on lead I and lead II of a dual channel ambulatory ECG recording. **rS** represents a very small R wave followed by an elongated S wave.

In RBBB, the right bundle branch fails to conduct the cardiac impulse; the impulse instead travels though the left ventricle to the right ventricle and depolarizes it. This altered conduction pathway takes more time as compared to the depolarization by the right bundle branch itself; as a result the QRS complex is widened. Deflections are also seen in the QRS complexes which reflect asynchronous depolarization of the left and right ventricles. Chronic pulmonary diseases, cardiac disease such as hypertension, coronary heart disease are the leading causes of RBBB.

In LBBB, the impulse first conducted by the right bundle branch, depolarizes the right ventricles and then travels down to depolarize the left ventricle. The impulse movement in the left bundle branch is away from the positive lead which results in an inverted QRS complex formation in the ECG. Long term cardiac diseases, hypertension, acute MI and other cardiac diseases may be the cause of this block. The ECG manifestation of LBBB is shown in fig. 3.

C. Continuous Wavelet Transform

The technique of Wavelet Transform conveniently converts a time domain signal to time- scale domain in which the changes in frequencies can be localized with respect to time and that too, efficiently. Wavelet transforms, when applied to bio physiological signals such as ECG, can effectively pinpoint the deviations in frequencies of cardiac waves from normal cardiac patterns. The wavelet transform mainly operates on the principle of Scaling and Shifting. The analyzing wavelet or the mother wavelet is convoluted with the whole of the time domain signal by shifting it along the length of the signal [4]. This process is also called translation. Upon completing the whole range of the signal, the mother wavelet is scaled and then the operation of shifting is repeated again along the length of the signal being analyzed. It can be mathematically summarized by the following equation:

$$X_{\omega}(a,b) = \frac{1}{a}\int_{-\infty}^{\infty} x(t)\ \psi*\left(\frac{t-b}{a}\right) dt \tag{1}$$

Where $\psi(t)$ is continuous in both time and frequency domain and $x(t)$ is continuous, square integrable function at a scale $a > 0$ and translational value b .

D. Neural Networks and ECG

The basic idea of neural networks is extracted from central nervous system (CNS) where the biological neurons are replaced by simple artificial neurons called Neurodes (Neurodes = Neurons + Nodes). An Artificial Neural Network (ANN) is configured for a specific application, such as pattern recognition or data classification through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. There are two kinds of pattern recognition techniques

1) Supervised : The input pattern is a member of a predefined class
2) Unsupervised: The input pattern is a member of an unknown class.

Recognizing an ECG pattern is the process of extracting and classifying ECG feature parameters, which may be obtained either from the time domain or its frequency domain information. Extracting and classifying, as we know is the essence of pattern recognition. Here, we have taken two categories of heart blocks (AV and BBB) and applied Neural networks to classify the patients according to their respective blocks. Compared to the traditional clustering methods, the artificial neural network models have good adaptive ability to environmental changes and new patterns and the recognition speed of neural network is fast owing to its parallel processing

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capability [5]. The performance of the neural network mainly depends on the selection of feature vectors.

II. Wavelet Based ECG Delineator

A wavelet based ECG delineator is used to extract the individual cardiac cycles from the long term ECG recordings. The time domain ECG signal is transformed to time- scale

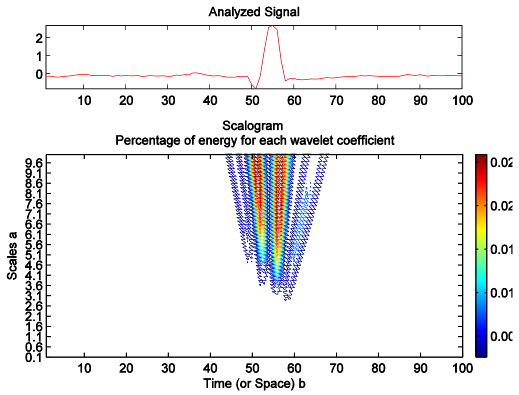

Figure 4: The scalogram representation of a single cardiac cycle ECG for a scale range of 1 to 10 using symlet 6 family of wavelets.

domain by the application of Wavelet Transform. It is found that the QRS complexes and hence, the R peaks lie in the scale range of 1 to 10 for arrhythmic signals [6]. The time domain plot of an arrhythmic cardiac cycle along with its scalogram (a time- scale representation for transformed time domain signals) is given in fig. 4. It can be clearly seen that the start and end of QRS complex is captured within a scale range of 1 to 10. The start and end of the complex in the time domain plot corresponds to the red complexes formed in the scalogram, which are actually the highest wavelet coefficients generated for that time domain signal. Figure 5 plots multiple time domain cardiac cycles and its corresponding scalogram. It reinforces our belief that the start and end of the QRS

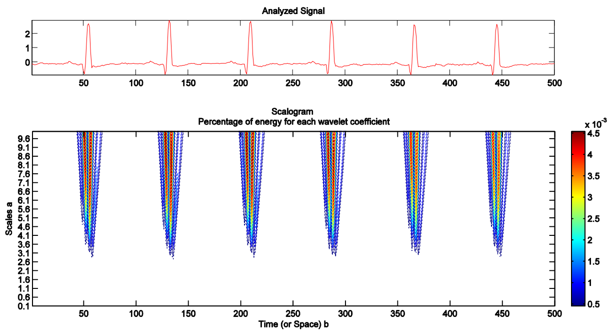

Figure 5: The scalogram representation of multiple cardiac cycle ECG for a scale range of 1 to 10 using symlet 6 family of wavelets.

complex for an arrhythmic cardiac cycle indeed generate the highest wavelet coefficients, which lie in a scale range of 1 to 10. This reduced scale of time- scale analysis firstly reduces the computation time and secondly reduces the size of the coefficients generated, bringing the performance of CWT at par with Discrete Wavelet Transform (DWT). The maximum value of wavelet coefficients generated is taken as reference against which the other R peaks are located from the time domain ECG signal. The other R peaks are located with respect to this reference value by allocating a certain threshold which acts as cut-off condition for the location of the other peaks. Once the R peaks are located, the start and end of the QRS complexes for each cardiac cycle corresponding to each R peak are located followed by the deduction of the position of the P and T waves with respect to the QRS complexes [7][8].

Once the cardiac cycles are extracted using the delineator, these cardiac cycles are used as feature vectors for input into the neural network classifier.

III. Methodology

The signal data for this paper is taken from the MIT-BIH Arrhythmia database. The signals are sampled at 360 samples per second with a resolution of 11bits over a range of 10 millivolts. The signals are dual channel ambulatory ECG recordings, collected from patients of various age groups and both genders [9] [10].

The database is scanned for patients with AV blocks and Bundle Branch blocks. The record numbers 108, 228, 231 and 232 are found to have higher degrees of AV blocks whereas the records 109, 111, 212 and 214 are found suffering from significant Bundle Branch blocks. The two cases of blocks were treated as two separate classes for classification by a neural network classifier.

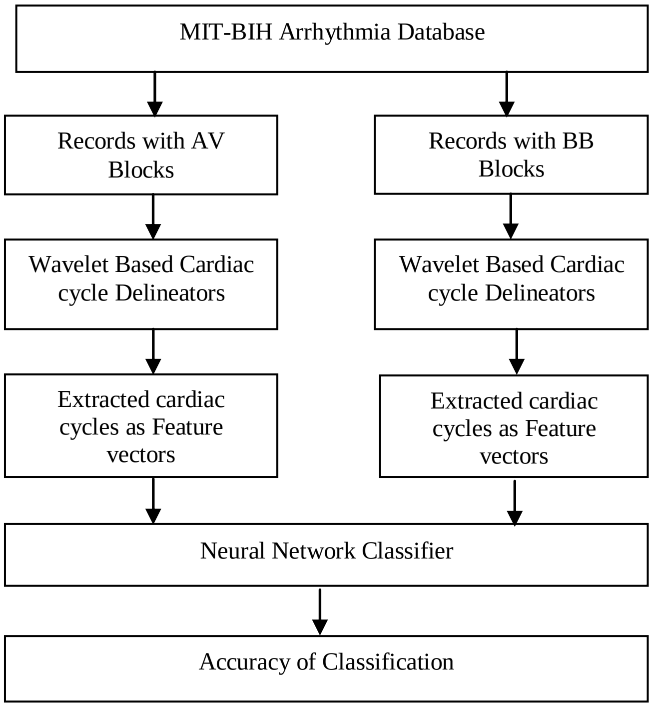

Figure 6: A flowchart, listing the stages used for classifying AV blocks from Bundle Branch blocks

In the first run, the time series ECG data from the aforementioned two classes are used as input for the neural network classifier. In the second run, the signals from both classes of blocks are passed through a wavelet based cardiac

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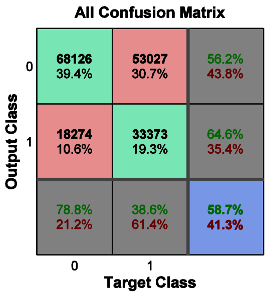
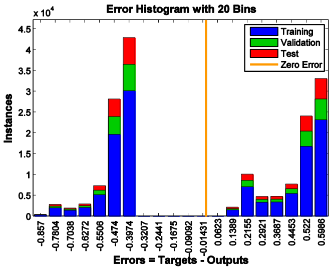
cycle delineator which detects and extracts individual cardiac cycles. Each of these extracted cardiac cycles is used as feature vectors for the neural network. The flowchart in fig. 6 shows this approach. The classification accuracy and error of classification during each epoch of the neural network are recorded. The accuracy of classification is shown with the help of a confusion matrix and the error in classification is represented by an error histogram in the next section.

IV. RESULTS

The time series classification of AV blocks and Bundle Branch blocks generated an accuracy of 58.7%. The corresponding error rate of 41.3% is significantly higher and it renders this method useless for actual classification of these blocks. The confusion matrix and the error histogram for this case are shown in figs. 7a and 7b respectively.



(7a)



(7b)

Figure 7a: A confusion matrix representation of the performance of the classifier. The box at the bottom right corner of this matrix gives the final accuracy of the classifier using the Time series based method of classification.

Figure 7b: An error histogram of the classifier performance for classifying between the two classes of data. It is evident from the histogram that there is no clear distinction between the two data classes.

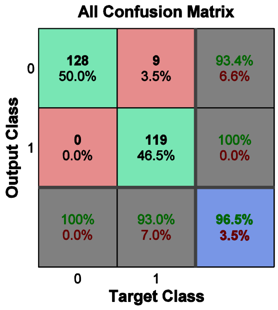
The use of individual cardiac cycles as feature vectors for classification provide more useful results with a stark increase in accuracy and a lower error rate. This method provides an accuracy of 96.5 %, which is significantly better than the previous case and it also provides a more realistic method for classification of AV blocks from Bundle Branch blocks. The confusion matrix and error histogram for this case are shown in figs. 8a and 8b respectively.

V. CONCLUSION

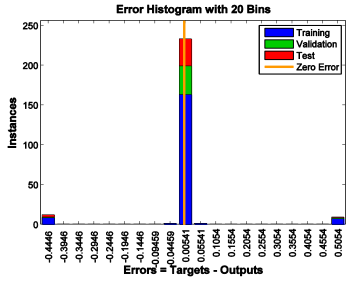
It is clear from the histogram that, for classification of the normal time series ECG data, the classifier encounters lots of misclassifications and hence a higher error rate is generated. It is primarily due to the fact that cardiac blocks may or may not affect the whole ECG signal. In most of the cases, the blocks may alter the behavior of the normal ECG signals minutely, which may not be detected or considered while calculating the mean and standard deviation of the signal for classification. It is clear from the histogram in fig.7b that the classifier couldn't differentiate between the two classes as their average behavior is similar. On the other hand when the individual cardiac cycles are used as feature vectors for classifying AV blocks and Bundle Branch blocks, the error rate is almost close to the zero error line signifying lesser misclassifications and sturdier feature vector selection. The error histogram for this case is shown in figure 8b. The classifier can easily differentiates between the two classes of signals representing two different cases of blocks using this method.

VI. FUTURE WORK

In the future, we plan to increase the data size, as the patient records with the required condition were limited in the MIT-BIH Arrhythmia database, so that we can get better and more accurate results for this approach. This method will also be applied on ECG signals for classification Left Bundle Branch blocks from Right Bundle Branch blocks.



(8a)



(8b)

Figure 8a: A confusion matrix representation of the performance of the classifier. The box at the bottom right corner of this matrix gives the final accuracy of the classifier using the wavelet delineated cardiac cycle based method of classification.

Figure 8b: An error histogram of the classifier performance for classifying between the two classes of data. It is clear from the histogram that the error is classification is very low and the classifier clearly distinguishes between the two data classes.

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