DETECTION AND IDENTIFICATION OF LBBB AND RBBB RHYTHMS IN ECG WAVES USING GABOR TRANSFORM ANALYSIS

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ABSTRACT -Automated analysis of ECG signals has evolved over a period of time to provide very sophisticated system analysis and interpretations. As the demand in the medical field is moving towards fully automated and intelligent systems, better technology and methods are required to interpret the abnormalities of body, especially of heart. Abnormal rhythms like LBBB and RBBB may not be life threatening but an early detection of these can avoid further complications. Here we present a signal processing approach to detect and identify L, R rhythms in ECG signals for early warning. Gabor transform technique is used for the analysis of the signal and the approach is capable of detecting the abnormality with sufficient accuracy.

Index Terms— ECG, LBBB, RBBB, STFT, Gabor Transform

1. IINTRODUCTION

Electrocardiography (ECG) is the process of recording the electrical activity of the heart using sensitive electrodes. An ECG signal can provide a good insight into the functioning of the heart. The effective depolarization of the ventricle mass cells requires that there be a specialized conduction pathway within the ventricle. Ventricular conduction system is divided into right and left Bundle branches after Bundle of His. Blocks can occur in this bundle branches and can results in Left bundle branch block (LBBB) and Right bundle branch block (RBBB). In RBBB the right ventricle is activated with a time delay after left ventricle. Because of this, the contraction of ventricle is also delayed and this can be observed as a significant change in ECG. QRS signal will be prolonged and there will be appearance of _bunny ears' in V1 and V2 leads. In LBBB the left ventricle depolarizes with small time delay after the right ventricle. The QRS will be prolonged with Leads I and V6 will record long R waves. A larger R' like an odd pair of _Bunny ears will be visible. In v1 lead, the R wave will be very small and S wave will be prolonged. It may become _Bunny eared'. In both the cases T- wave will be abnormal. The block can be caused by coronary artery disease, cardiomyopathy, or valve disease. Even though the bundle branch block itself may not be a problem, it can be a warning sign of other, more serious heart conditions. How to detect the occurrence of RBBB and LBBB in an automated way remains to

be challenge and very deep investigations are on way. The detection of phenomenon based digital signal processing techniques are under development in various laboratories. In order to solve this Gabor Transforms can be a candidate technology. The Gabor transform is a special case of the short-time Fourier transform (STFT). This transform can be used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time. In STFT the signal to be analyzed is divided into frames and each frame is Fourier transformed, which provides magnitude and phase for each segment. As the window is moved along time we will get a two dimensional matrix   in   time   –   frequency   domain. $\text{STFT}\{x(n)\}(m, \omega) = \sum_{n=-\infty}^{+\infty} x[n]w[n-m]e^{-j\omega n}$. The magnitude squared   of   the   STFT   yields

the spectrogram of the function. In Gabor transform the window used is a Gaussian function and the resulting function after multiplication is then subjected to Fourier transform to derive the time-frequency analysis. The window function means that the signal near the time being analyzed will have higher weight. The Gabor transform of the signal x(t) is given by $G_x(t, f) = \int_{-\infty}^{\infty} e^{-\pi(\tau-t)^2} e^{-j2\pi f\tau} x(\tau) d\tau$. The Gaussian window parameters can be adjusted to extract the required features.
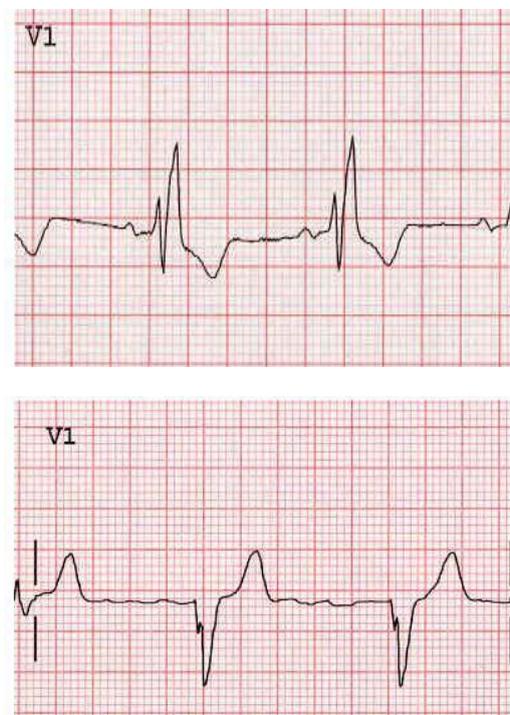

Fig1. (a) RBBB   (b) LBBB

Yu et. Al [1] has used discrete wavelet transform for feature extraction. Three sets of statistical features of the decomposed signals as well as the AC power and the instantaneous RR interval of the original signal are exploited to characterize the ECG signals. In [2] authors have   used

QRS pattern recognition method for computation of a large collection of morphological QRS descriptors and Matching Pursuits algorithm for classification algorithm, Huang et.al has developed a method to classify LBBB and RBBB from normal beats. They used a combination of three different types of classifiers: a minimum distance classifier constructed between NORM and LBBB; a weighted linear discriminant classifier between NORM and RBBB based on Bayesian decision making using posterior probabilities; and a linear support vector machine (SVM) between LBBB and RBBB. Their method predicted a sensitivity of 91.4% for LBBB and 92.8% for RBBB. In [2] authors have extracted the features like QRS duration, R-R interval etc. and used a Multilayer Perceptron (MLP) classifier. Amandeep et.al used stationary wavelet transform to extract the features for classification.

2. RESEARCH BACKGROUND

Automatic analysis of ECG is gaining momentum over a period of time. With the advancement in technology faster and accurate methods of analysis is required for meeting the present day requirement in telemedicine and automated Biosignal analysis. Even though LBBB and RBBB are not a life threatening abnormality, it is an indicator of hidden problems related to heart. A timely detection can prevent further complications. There are many methods which were adopted for the classification of beats of normal rhythm, LBBB, RBBB, PVC etc. Most of these methods adapted Fourier transform or wavelet features for classification. In most of these cases neural network, principal component analysis, and different classification algorithms are used. But in case of LBBB and RBBB, the major requirement is to know the presence of LBBB and RBBB over normal rhythm which is sufficient for further investigation. After detecting LBBB or RBBB, deeper analysis may be required to find the hidden cause, by seeking the expert advice of a physician.

In this work, our aim was to detect the presence of LBBB and RBBB in comparison to normal rhythm. For this we have used the time frequency analysis STFT using Gaussian window. Gaussian window parameter center frequency and standard deviation give the flexibility to extract the required parameters from ECG waves.

3. RESEARCH METHODOLOGY

The required data for analysis is collected from the ECG signals arranged for analysis. It is collected from global data source where annotated ECG signals are available. MIT-BIH Arrhythmia diagnostic database was used for the testing of algorithm. MIT-BIH Arrhythmia Database provides a collection of 48 fully annotated half-hour two-lead ECGs. It also provides a database directory with a table of beat types. This provides enough data for testing and since each beat is annotated the verification was easy. ECG data strips for 10 sec were collected and each one was analyzed separately. Before any ECG feature extraction the first step should be to remove the noises. The main noise which can affect the detection is the baseline wandering. So we have used median filters to remove baseline drift.

Baseline Drift Removal

Any ECG signal analysis requires a pre-processing to remove the noise artifacts. For a computerized detection of ECG features the main affecting noise factor will be the baseline drift. The frequency content of the baseline wander is usually in a range well below 0.5Hz. This baseline drift can be eliminated using median filters (200-ms and 600-ms). The original ECG signal was processed with a median filter of 200-ms width to filter QRS complexes and P waves. The resulting signal was then processed with a median filter of 600-ms width to remove T waves. The signal resulting from the second filter operation contained the baseline of the ECG signal, which was then subtracted from the original signal to produce the baseline corrected ECG signal. The baseline corrected signal for the ECG signal 108 V1 lead is shown in fig 2. The intermediate results of unravelling QRS & P-wave as well as T-waves are also shown in Fig 2.

The base line corrected signal is then subjected to short time Fourier Transform using Gaussian window. Simulation was carried out in MATLAB. Gaussian window with varying standard deviation and centre frequency were used and found the optimum values to get a spectrogram which enhances the LBBB and RBBB frequency bands.
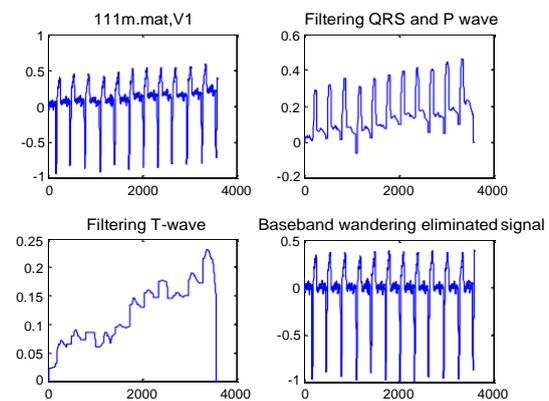

Fig 2. Base drift eliminated signal

4. RESULT

The proposed algorithm was tested on MIT-BIH arrhythmia database. MIT-BIH database consists of 9 records, each of 30 minutes duration with two simultaneous channels sampled at a frequency of 360Hz which has LBBB and RBBB beats. Each record was tested for LBBB and RBBB presence and found to be detecting it. Spectrogram was able to give the location and the presence of each LBBB and RBBB over normal rhythm. Fig.3. Below gives the spectrogram of three signals with LBBB, RBBB and normal rhythm. From the spectrogram it can be seen that for RBBB the significant frequencies are less than three Hz. In LBBB case the significant spectrogram frequency is above 4Hz. In normal rhythm case the significant frequencies are above 10Hz. Here the Gabor Transform analysis over ECG signal yielded a comprehensive frequency perspective of the performance of heart indicating vital deviation from normal performance in a graphical way. Fig 3 shows the three different cases considered for analysis. A normal waveform,

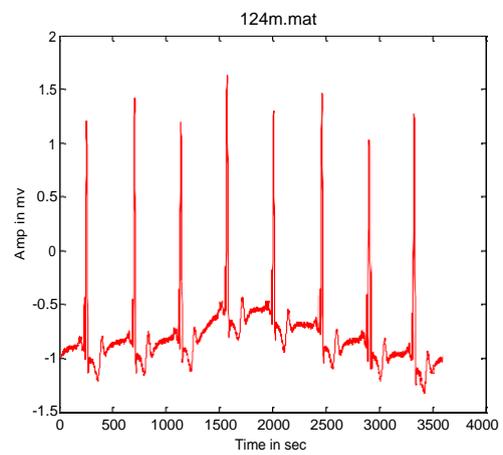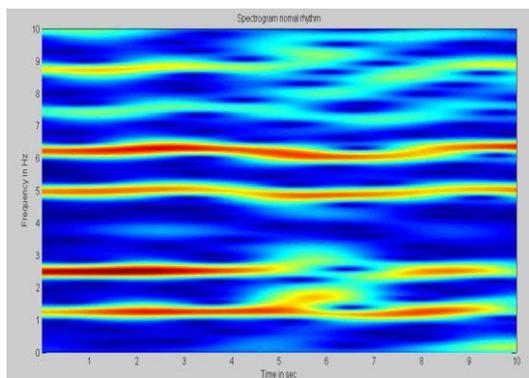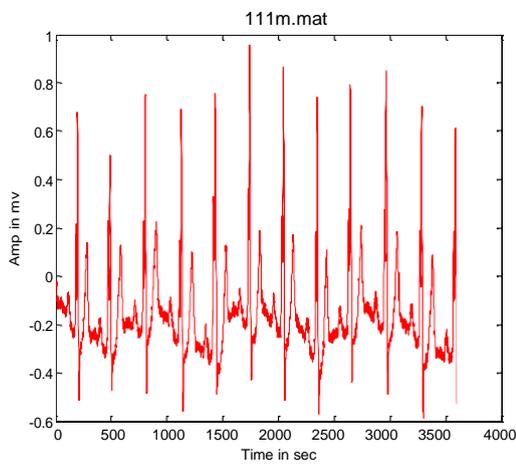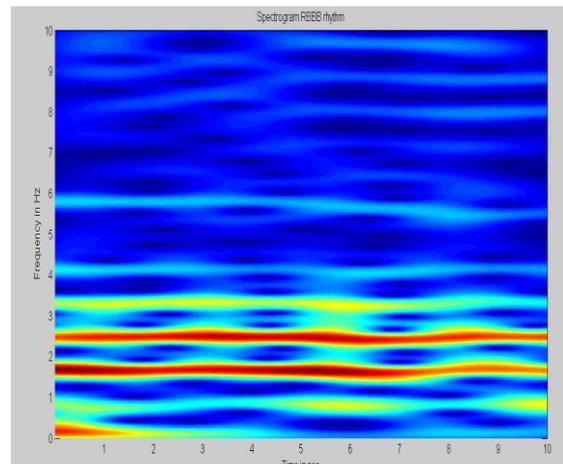LBBB and RBBB rhythms with their corresponding spectrograms are shown here.
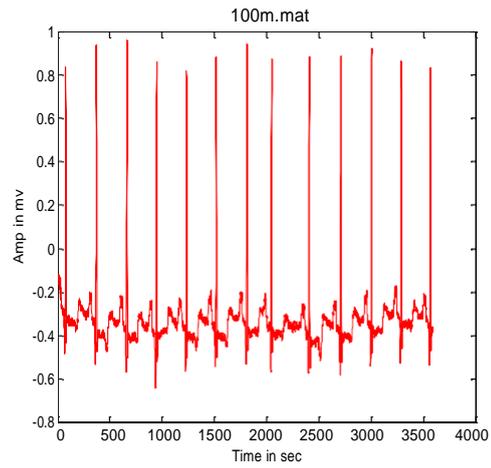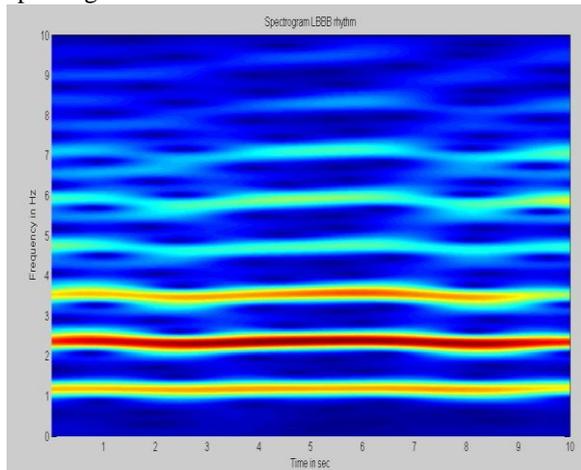

Fig 3. a) LBBB b) Normal Rhythm c) RBBB

5. CONCLUSION

The method of applying Gabor Transform for ECG signal analysis has enabled the detection of time sequenced frequency fluctuations occurring in ECG signals. The method of identifying LBBB, RBBB rhythms as presented here was found to be efficient for detecting those phenomena. This yielded a definite improvement on ECG analysis bringing viability to automated detection of ＿L R' rhythms. More study is required to identify the further scope of this approach by closely observing ECG variations.

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