Implementation of ECG QRS Detection Method using Python

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***Abstract*—QRS waves are nothing but the Q wave, R wave, and S wave combinations also known as ventricular depolarization. There are multiple ways to detect QRS waves in ECG (Electrocardiograph Signals). This paper discusses one such method called the Pan-Tompkins algorithm implemented in python to detect QRS waves in ECG signals. This feature helps measure the heart rate easily as QRS waves are the main spikes visible in ECG signals.**

Keywords—QRS waves, ventricular depolarization, ECG signals, Pan-Tompkins, heart rate.

I. INTRODUCTION

The QRS waves are the combination of Q, R, and S waves. Heart problems such as arrhythmias, conduction abnormalities, and ventricular hypertrophy can be detected with the help of the duration, amplitude, and morphology of QRS complexes. Detecting the QRS waves have a huge significance in clinical history [1]. It is considered crucial to accurately detect QRS waves in ECG.

Since ECG data is used for clinical purposes, thus there are grave consequences in case of inaccurate readings. Roughly 2.4 million Canadians which is 1 in 12 Canadians live with heart disease of the age group 20 and above. There is a record of 1 in 12 Canadians die due to heart disease every hour [2]. Thus, it is was a necessity to accurately design a system to detect QRS waves in ECG. We have implemented the Pan-Tompkins algorithm in this paper to detect QRS waves in ECG.

The multiple types of noise that can be present in ECG signals makes it generally difficult to detect QRS signals. The noise is influenced by the muscle movement, low frequency found in the ECG signal (BW), and the T-waves with high-frequency characteristics [3]. We have implemented the algorithm discussed in [3] with help of python code. We feed recorded ECG signal data as input to the detector. The detector processes the signal and does filtering and thresholding to reduce noise from the data. We only chose to implement the core features needed for QRS detection from [3] and excluded supplementary features.

II. LITERATURE SURVEY

This paper [4] discusses a sleep-related breathing disorder known as "sleep apnea" which normally occurs in middle aged adults. This paper presents a simple system to identify the above disease from ECG signals. A linear transformation method known as Principal Component Analysis (PCA) is applied to QRS complexes. The role of PCA is to segment the QRS complex based on the width of the QRS complex and consider its amplitude as well as modulation of R-peak to derive the mean variation. Three different algorithms were also used to find out ECG-derived respiration and their results were compared. The first algorithm is the usage of R-peak and the second one is using PCA and the third one is the Kernel version of PCA. Different classifiers like Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Least Square SVM (LS-SVM) were used in this paper. LS-SVM was found to outperform other classifiers by giving an accuracy of 90% because using this classifier, the authors were able to eliminate bias from the source by including QRS segments with higher confidence levels in the training data.

This paper [5] discusses an algorithm to reduce the noise which might be caused as a result of motion in ECG signals by maintaining the power of the original signal within the QRS peak interval and reducing noise power at other intervals. The noise in the ECG signal can distort R-peak detection. By using the robust variable step size affine projection sign method, this paper proposes a new Adaptive Noise Cancellation structure which does not affect impulsive noise and thereby, power of ECG signal is processed to detect the QRS interval and the noise is minimized to improve the R-peak detection.

The rate of the heartbeat is hampered due to an arrythmia. During an arrhythmia, the heart can thump excessively quickly, too gradually, or with an unpredictable mood. This paper [6] discusses on curvature-based vertex selection method to solve the enigma of fiducial points in QRS complexes. The authors initially use curvature-based polygonal approximation to select vertex and then perform incremental vertex selection using repetitive sequential polygonal approximation and finally with the help of dynamic programming they perform an additional vertex optimization step. Test results show that the proposed helper signal-based strategy empowers stable identification for different applications in genuine ECG information bases furnished with QT-DB and MIT-BIH ADB.

III. PROPOSED METHOD

In this paper, we implement the Pan-Tompkins proposed algorithm to detect QRS peak from ECG signals based on [3]. We consider the raw ECG signals data taken from the GitHub repository shared below as an URL as an input to our detector. https://github.com/KChen89/QRS-detection/blob/master/

Total of 6030 ECG measurements were considered. We know that there might be noise associated with ECG signals when recorded. To eliminate the measurement noise from the signal, we subject our data through two main stages namely filtering and thresholding.

In the filtering stage, the signal is filtered by the bandpass filter. The filtering stage helps to eliminate most of the noise from the data that has the possibility of causing false detection. Hence the filters help to ensure that only part of the signal related to heart activity can pass through. Differentiating the obtained bandpass filtered signals helps to identify signal parts with high signal change values. We then square and integrate them to make the signals more distinct. We then apply the peak detection algorithm to the integrated signal to detect QRS complexes within the integrated signals.

We set a base threshold to classify the identified QRS complexes signals as either QRS complexes or noise peaks dynamically. The thresholds are adjusted as per real-time and is based on signal values of previously detected QRS or noise peaks. Change in noise peaks is accounted for by dynamically changing threshold value. The dynamical thresholding and complex filtering ensure sufficient detection sensitivity with few false-positive QRS complex detections.

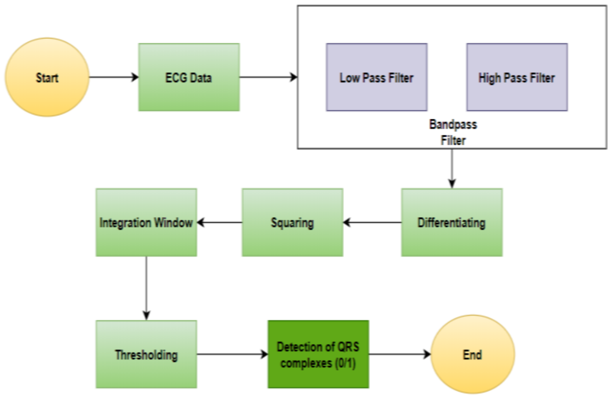

Fig 1: Flowchart of QRS detector based on Pan-Tompkins algorithm

The QRS complexes detected are stored in the log file in the local system. We mark 1 for those signals which were classified as QRS peaks in the log. Also, we plot the ECG signals for each stage and save the plot to the local system. The detector is most reliable, and we change parameters to different values and try to compare the results obtained. The noise in the raw ECG signal data is minimized with the help of a bandpass filter. This paper uses a bandpass filter in place of the low pass and high pass filter described in the original paper. The transfer function of the second-order low pass filter and the amplitude response is shown below [3] :

$$\mathrm{H(z)} = \frac{(1 - z^{-6})^2}{(1 - z^{-1})^2}$$

Equation 1: Transfer function of low pass filter

$$|H[wT]| = \frac{sin^2(3\omega T)}{sin^2(\frac{\omega T}{2})}$$

Equation 2: Amplitude response of low pass filter

The transfer function and amplitude response for high pass filter is shown below [3]:

$$H(z) = \frac{(-1 + 32z^{-16} + z^{-32})}{(1 + z^{-1})}$$

Equation 3: Transfer function of High pass filter

$$|H[wT]| = \frac{[256 + sin^2(16\omega T)]^{1/2}}{\cos(\omega T/2)}$$

Equation 4: Amplitude response of High pass filter

IV. Results

This paper presents you the implementation and design of a QRS detector in python using recorded ECG data. Fig 2 depicts the analysis of ECG signal at different stages of the digital signal processing. The noise in the raw ECG signal can be minimized by means of a bandpass filter. 4 noise peak and 27 QRS peaks were detected for below parameters mentioned.

A sampling frequency of 250 Hz, low cut-off frequency of 5 Hz, High cut-off frequency as 15 Hz, and filter order as 2 was used. It missed 15% [1-(27-4)/27)] of QRS peaks. The parameters can be varied and experimented with for different values. One could achieve optimum output when values are set properly. The differentiated signal gives the slope information of the waveform.

```
qrs peaks indices
[  23  300  501  702  904 1104 1305 1505 1717 1919 2109 2321 2913 3114
 3515 3729 3918 4119 4331 4520 4737 4934 5137 5339 5525 5737 5928]
noise peaks indices
[2521 2727 3038 3326]
```

Fig 2: The QRS and noise peak indices

The refractory period is set to 120 milliseconds, once the QRS complex peak is detected, there is a refractory period of 120 milliseconds to detect the next QRS peak. The possibility of false detection can be eliminated with the help of a refractory period. The signals at various stages of digital signal processing are plotted below in figure 3. The first stage shows the raw ECG signal read directly from the source. We can see baseline wander along with some noise in the signal. Stage 2 shows the output from the bandpass filter. The noise from the signal is minimized and the waveform is better than before. Stage 3 is the differentiated output of the filtered signal. It was done with the help of the NumPy library in Python. Output of this stage gives information on the slope of the waveform. In stages 4 and 5, the output is squared and Integrated to make the signal more distinct. The output of the stage 5 is compared with the threshold. The threshold is chosen keeping in mind the previous value of detected QRS and noise signal value. Each time the QRS signal detected is compared with the threshold. If the value is below the threshold, the signal will be updated as noise and will be marked as 0 in the log, otherwise the signal will be detected as QRS and will be marked as 1 in the log file. The use of a single threshold simplifies the entire process and the bandpass filter implementation using the Scikit Learn library from Python was very useful.

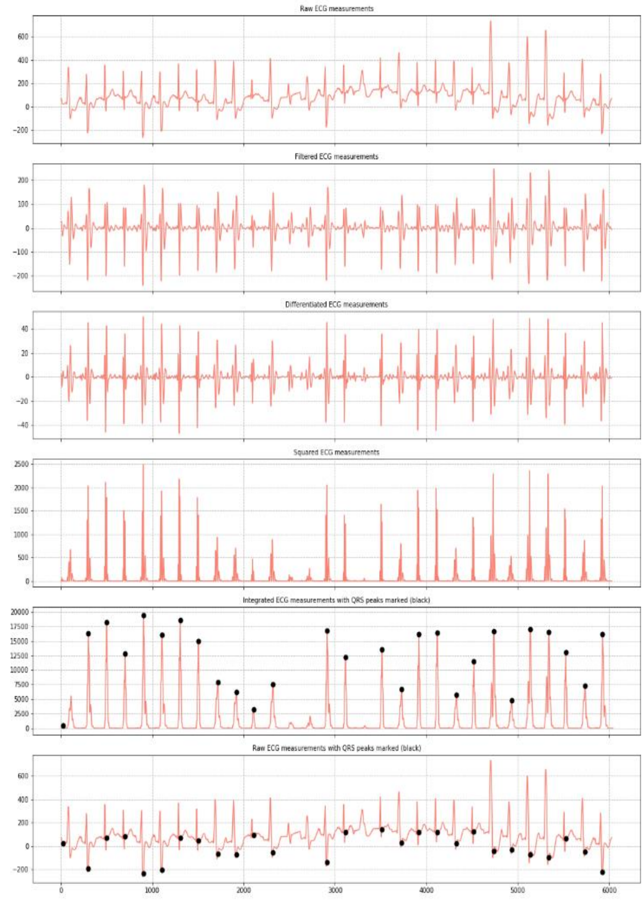

Fig 3: The plot of the signal at various stages.

V. DISCUSSION

The detection accuracy can be said to be 85% accurate than Pan-Tompkins approach of 90% because Pan-Tompkins used live ECG whereas we used recorded ECG data. Some difference will be present as the dataset varies; another possibility could be that we used only one threshold in this paper to reduce complexity rather than the original paper where 2 threshold values were used like a feedback loop. Experimenting with different parameter values yielded most of the times better detection of QRS peaks. This study also helps in retrieving logs of QRS detected peaks and plots to the local system to help view it anytime. In the original paper [3] two sets of thresholds were used, one at the end of the filtering stage and one at the end of the integration stage to increase the reliability of detection. In this paper, only one threshold is chosen and is applied for the moving window integrated output signal. The reason for choosing a single threshold instead of two thresholds because, in the original paper [3], the authors tried to use the low pass and the high pass filter whereas in this paper direct implementation of the bandpass filter is done to reduce the complexity of the program.

Further comparison with the paper [8], showed that the angle-based method could be more simple and robust than the Pan-Tompkins algorithm. In the paper [8], the slope of the ECG signal was represented by using geometric angle. The method adopted in the angle-based approach was able to remove completely high-frequency noise and determined R peaks using the adaptive threshold. The angle used in the paper is highly sensitive to high-frequency noise and thus could sometimes result in false detection of QRS peaks which is not the case in Pan Tompkins where several stages of signal processing are used to make sure QRS peaks are accurately detected.

VI. CONCLUSIONS

This paper presented a benchmark study on the analysis of ECG signals by detecting QRS using the Pan-Tompkins algorithm. A pre-recorded ECG data was used in this benchmark study and few python libraries. It was found that we get a better QRS peak if we can eliminate noise and baseline wander completely with the help of bandpass filters. Further, the study can be expanded by choosing the right parameters so that an even better QRS peak can be obtained.

This paper's approach to the Pan-Tompkins model does not include sensitivity or specificity because it does not use a machine learning approach. This paper uses a traditional approach like that of Pan Tompkins. It is possible to get metrics of the confusion matrix and find out features like sensitivity and specificity if the training data is modelled using a classifier. In the future, the study can be expanded to use real-time ECG data of patients and can be expanded to work with the ECG of multiple patients at the same time to detect QRS peaks.

ACKNOWLEDGMENTS

This work was done under Professor Raymond Wallace, Carleton University, Ontario, Canada. Lectures and notes of the professor helped to understand more about ECG signals.

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