# ASSIGNMENT – III

**ECG Signal Analysis**

**ADVANCED DIGITAL SIGNAL PROCESSING**

**(ELL-720)**

**SUBMITTED TO:**

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**Submitted by:**

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## Introduction

In this assignment, we are tasked with analyzing two digital ECG signals, ecg1 and ecg2, to estimate heart rates and QRS intervals for each heartbeat. Both signals consist of 650,000 samples, sampled at 360 samples per second. To better understand the data, we need to familiarize ourselves with the terms associated with different points in the ECG cycle.

Figure 1 illustrates these points, including the P, Q, R, S, T, and U points. The highest point in the cycle is the R point, and the time between consecutive cycles can be estimated by determining the time between two R points, known as the R-R Interval.

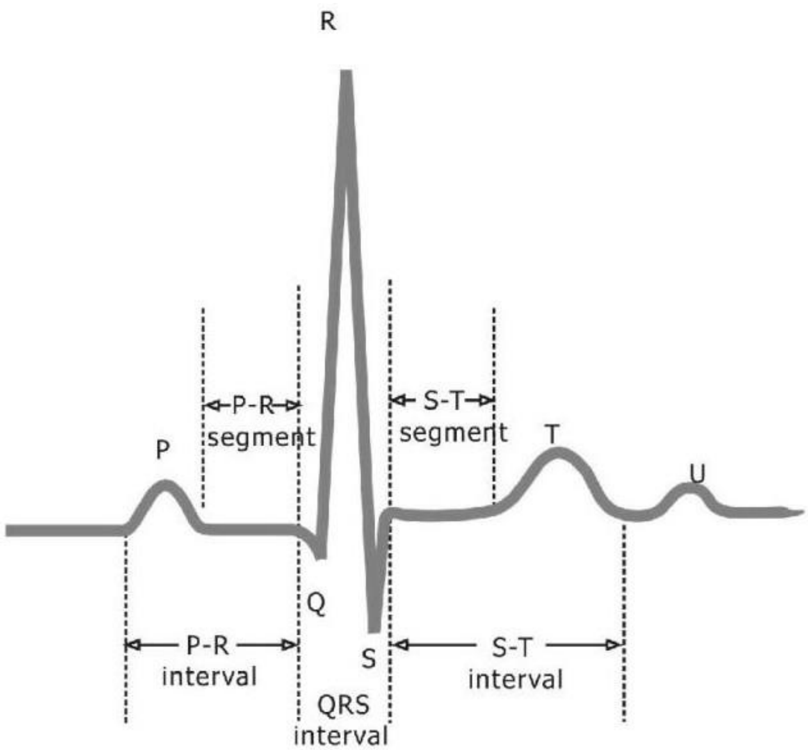



Fig 1. One cycle of ECG

Once R-R interval is determined we can calculate heart rate in beats per minute or BPM using the formula mentioned below

$$\text{Heart Rate} = \frac{1}{\text{R} - \text{R interval}} * 60$$

### Algorithm for heart Rate Detection

In order to determine heart rate, we need to determine R-R Interval, Implementation is based on the fact that second stage median filtering with window width and after that sixth order power shows a sharp peak around the R point. Steps involved in the algorithm are as follows:

Step -1: First stage median filtering with window width fs/2,

Step 2: Second stage median filtering with window width fs

Step 3: Removal of base line drift

Step 4: Enhancement of peak by sixth order power

Step 5: Find index of peaks above certain threshold

Step 6: Determine corresponding R-R interval, hence Heart Rate in BPM.

### BPM calculation:

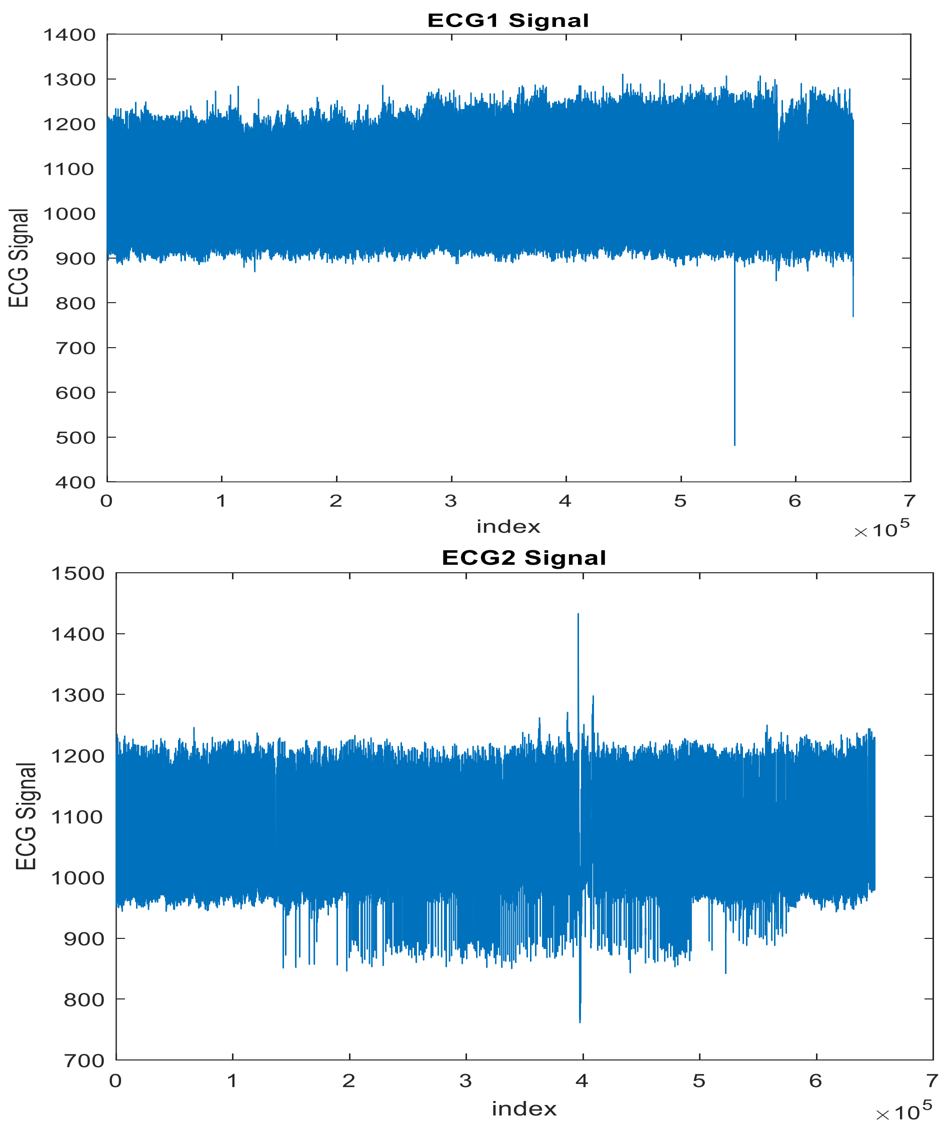



Fig 2. Raw data of ECG1 and ECG2

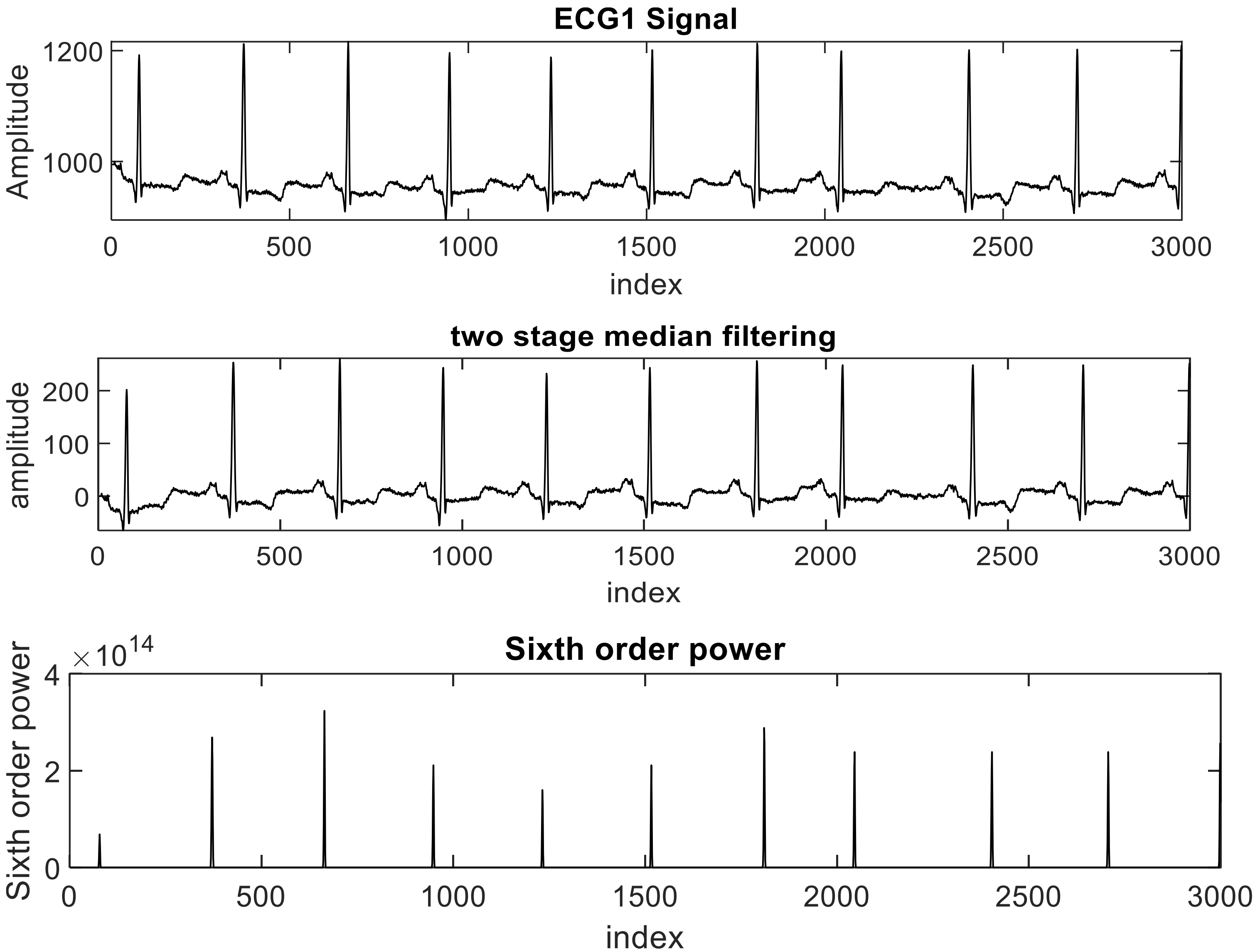



Fig 3. Enlarged view, two stage median filtering and sixth order power ECG1

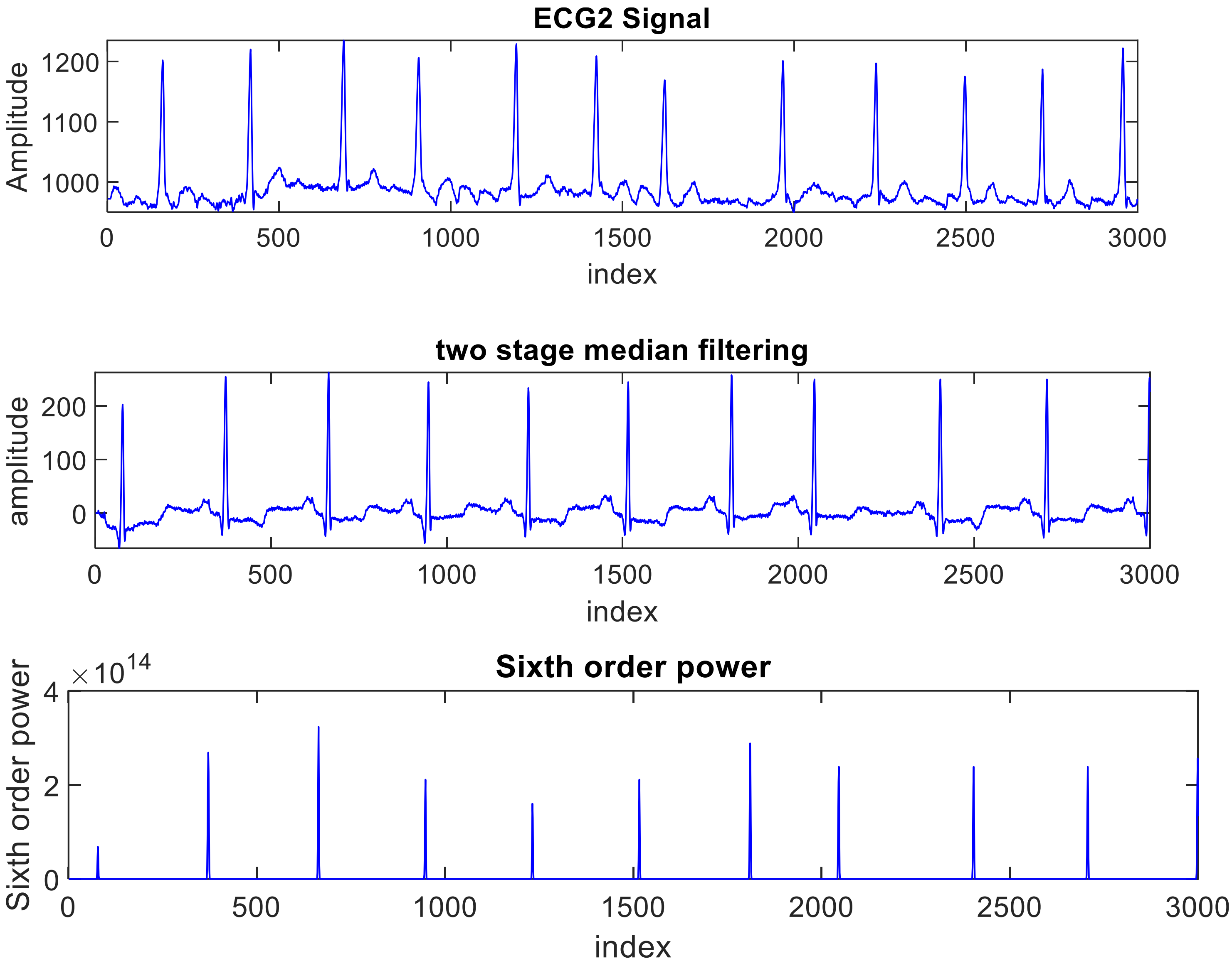



Fig 4. Enlarged view, two stage median filtering and sixth order power ECG2

Figure 3 and 4 shows first stage median filter with window size fs/2, second stage of median filtering with window size fs and sixth order power of ECG1 and ECG2 signals respectively and we can clearly see the sharp peaks at R points.

So, to get sharp peaks along the R points first we need to do the median filtering in two stages to remove the wander baseline drift and to align the signal with zero perfectly. further enhanced by point to point six time data multiplication where the sharp peaks such as Q, R, S are more enhanced than artifacts and P & T waves.

when searching for the R index for precise detection, a value greater than threshold which is taken by mean of enhanced signal is taken and index is taken corresponding to that value. After that we have calculated R-R interval and hence heart rates in beats per minute using formula stated before. We have assumed that heart rates greater than 120 BPM and less than are 40BPM are false detection, so have put an additional constraint to remove those.

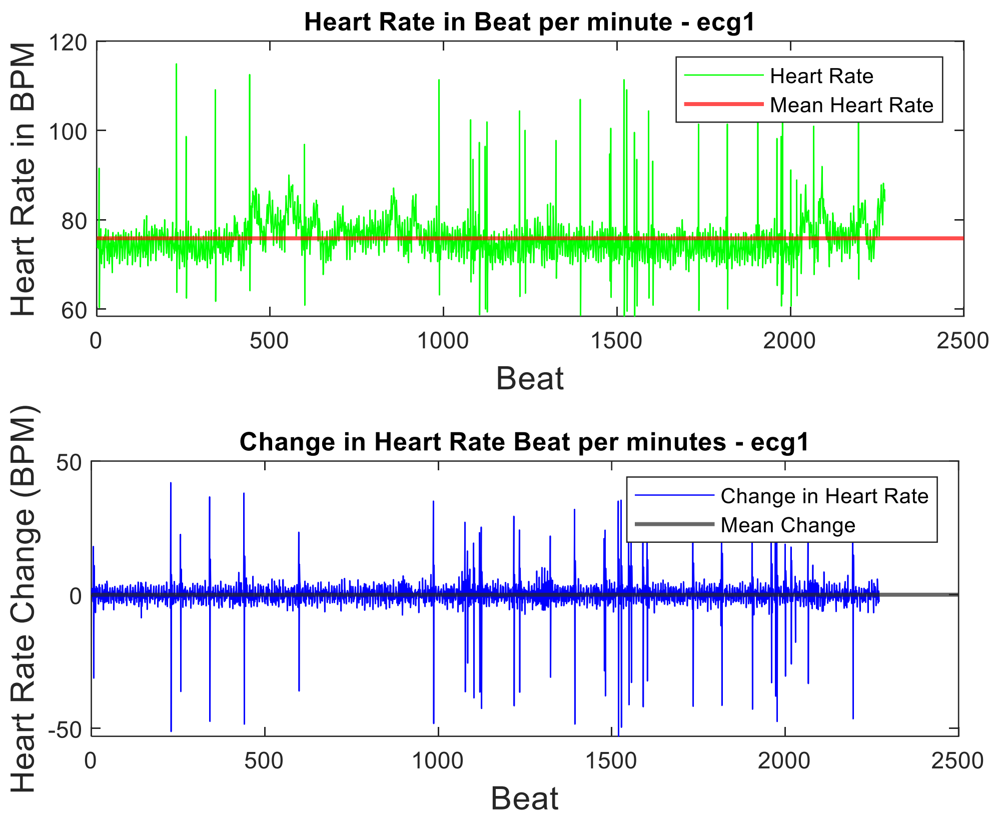



Fig 7. Heart rate and change in heart rate of ECG1

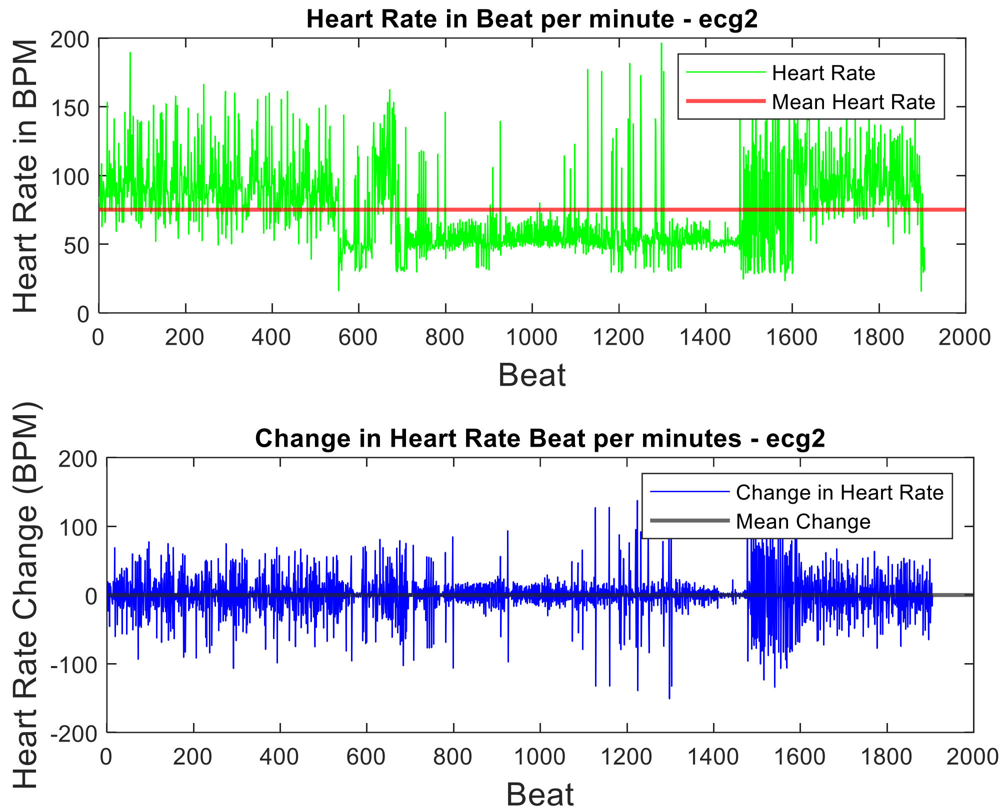



Fig 8. Heart rate and change in heart rate of ECG2

we've computed the beat-by-beat heart rates for both ECG files, as depicted in figure 7 and 8. In ecg1, the heart rates shows small variations with with less abnormalities, possibly stemming from false detections or inherent data anomalies. On the other hand, ecg2 displays highly irregular and abnormal heart rates, varying significantly beat by beat. Additionally, we've visualized the changes in heart rate beat by beat, illustrating a more consistent range for most beats in ecg1 compared to the erratic variations observed in ecg2.

According to histogram give below in figure 9 and figure 10, We can observe that most common heart rate for ecg1 is between 70-80 BPS, and distribution is even around it, with very few values of too high or too low heart rates, whereas in ecg2 most common heartrate is as low as 30- BPS but significant mount of times its quite high as well, and has a big distribution at different values suggesting very un-even heart beats We can also observe that heart range changes less often, and mostly by small magnitude in ecg1, but in ecg2 although at most instances, change is small, but significant number of times, changes are large as well.

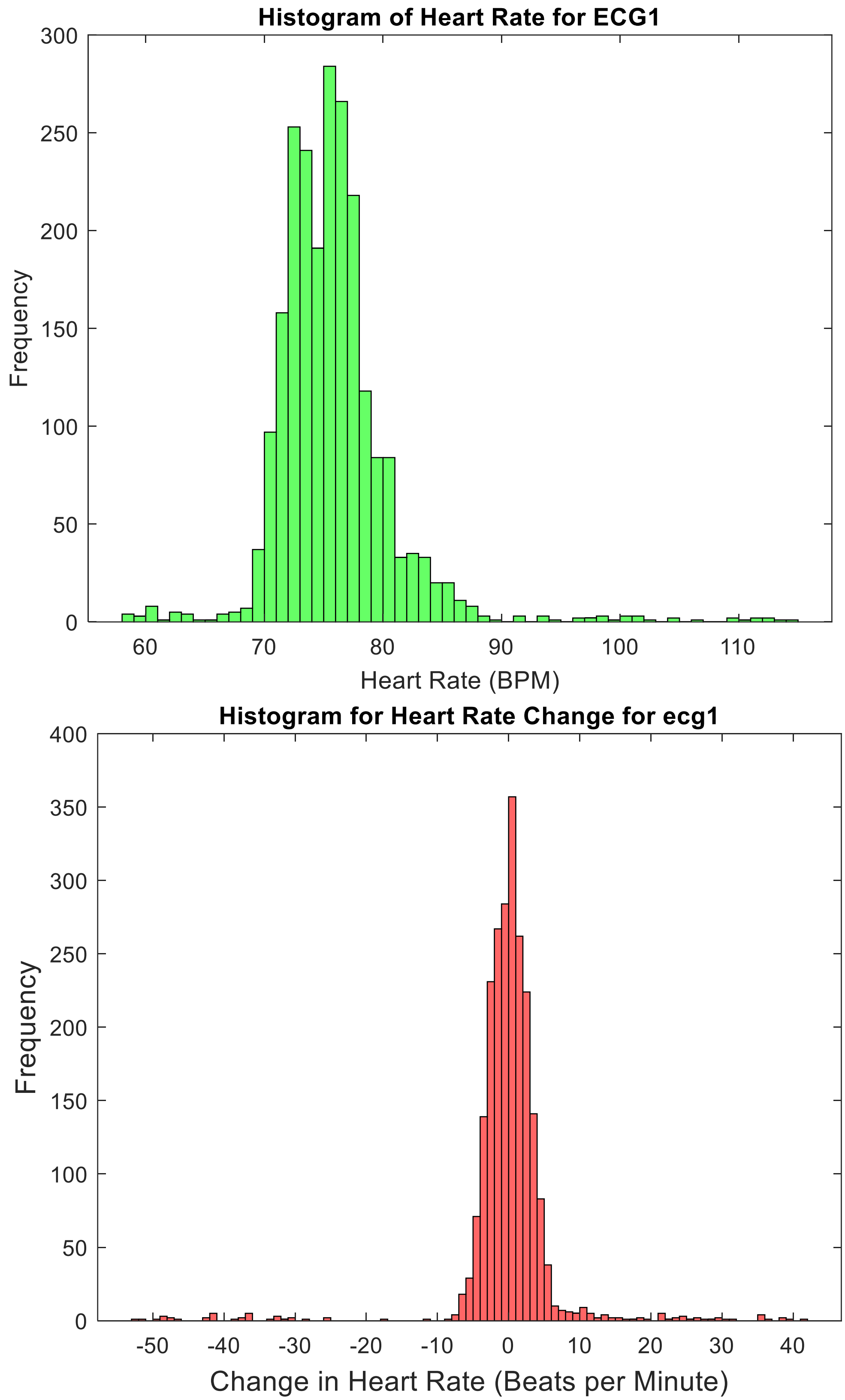
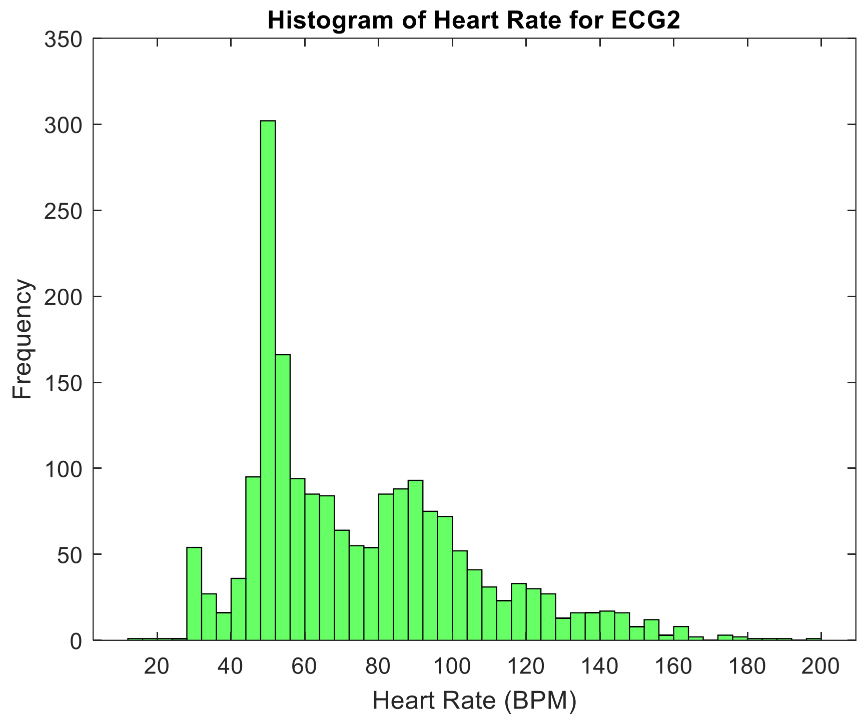



Figure 9. Histogram of Heart rate and change in heart rate of ECG1



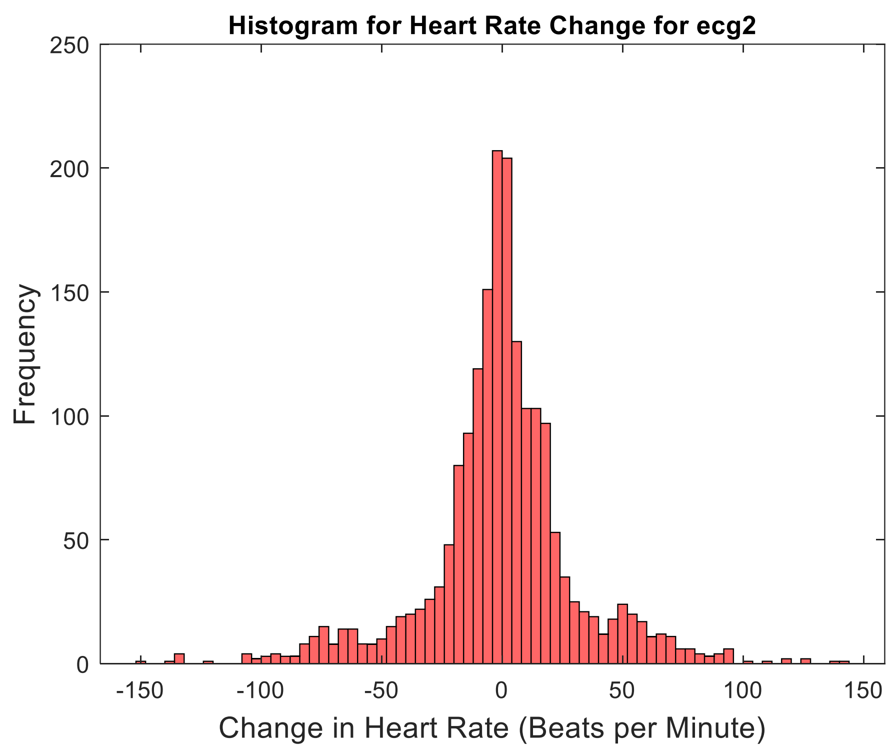
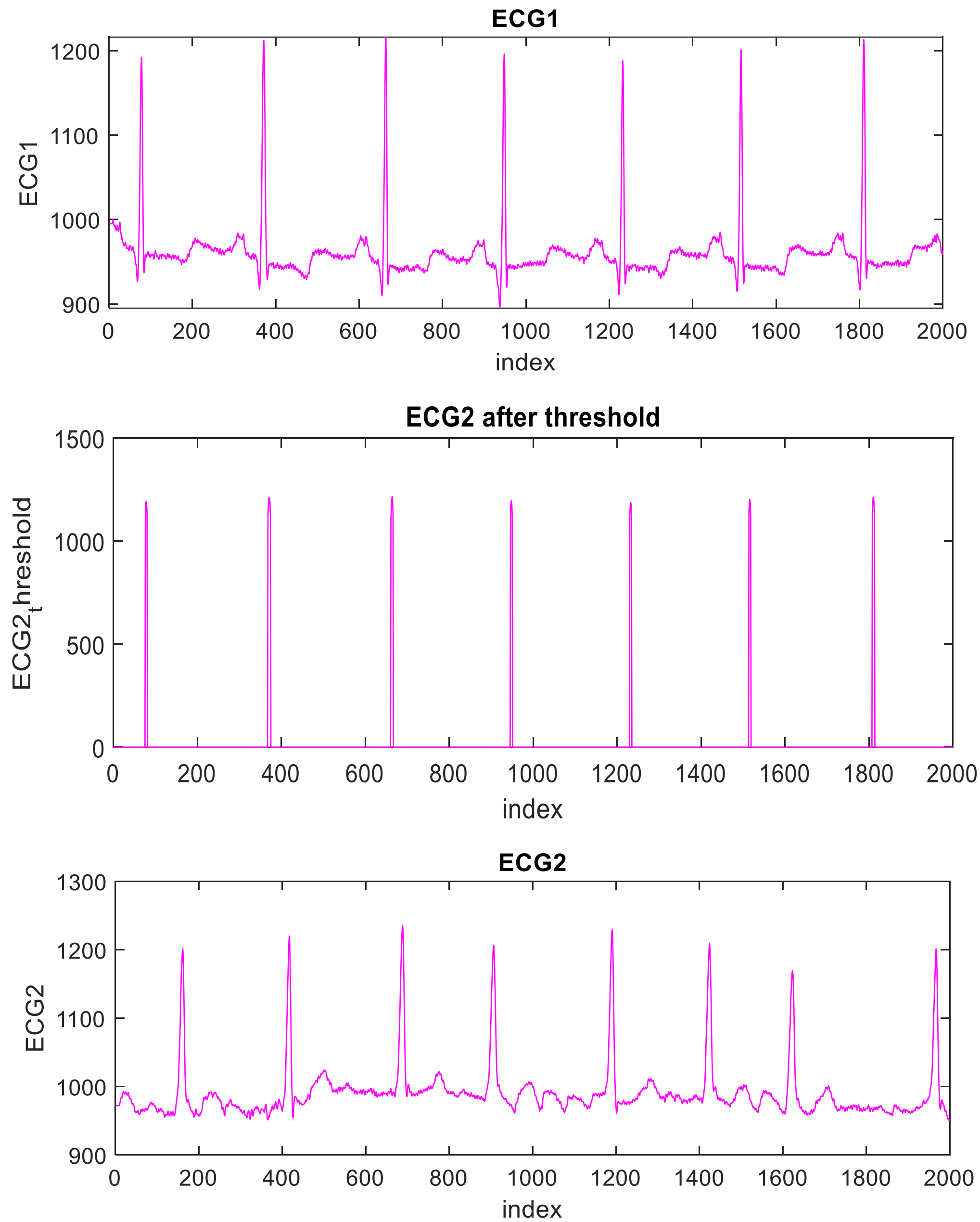




Figure 10. Histogram of Heart rate and change in heart rate of ECG2

**Visual method to validate BPM calculations by double differentiation method:** To check our result we have used visual method which involves visually inspecting the ECG signals and choosing a threshold. We first identify the peaks then noted indexes corresponding to those peaks and then do similar process as above mentioned. For this we have chosen threshold value of 1100 for ecg_1 and 1050 for ecg_2. This method is not very effective in case of ecg_2 as it has large variations in peaks that means peaks are not of same size so many of peaks may lie below threshold and they will not detected reducing the threshold to detect those peaks may consider noise so that is also not a vise choice.

Figure 11 illustrates the implementation of this visual method.



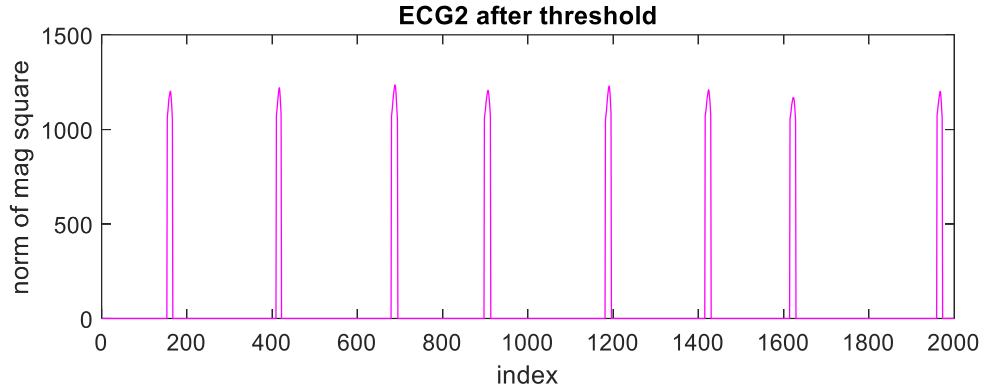


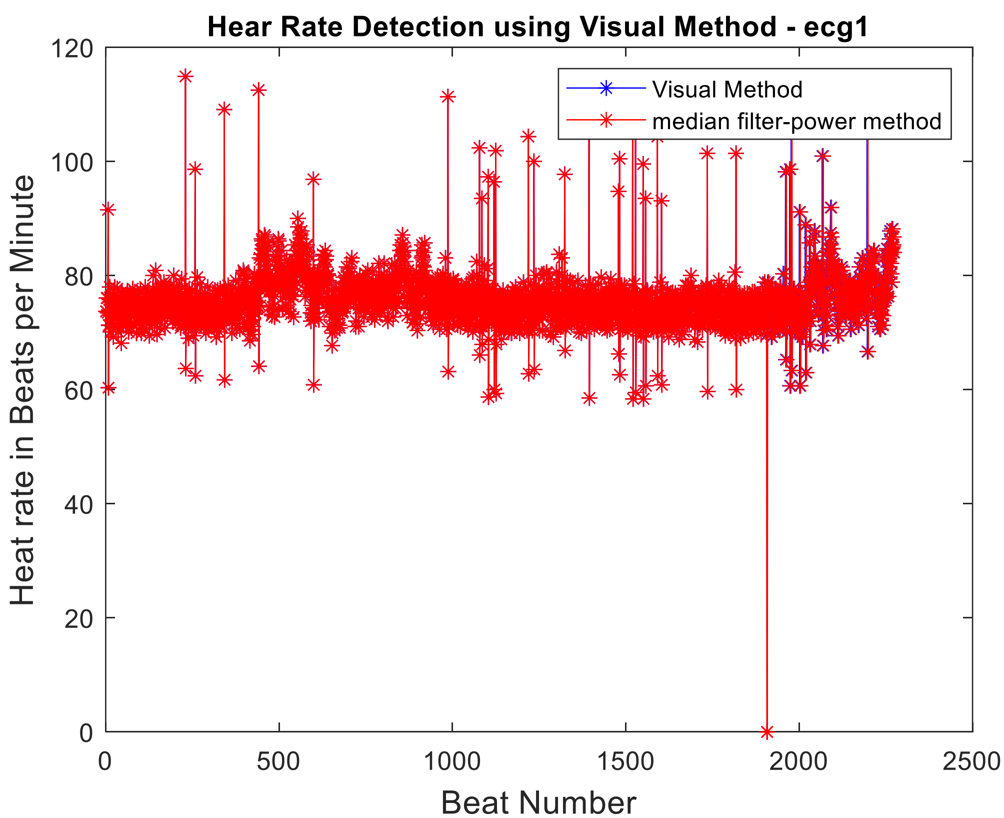

Figure 11. Visual method Implementation for ecg1 and ecg2

Upon implementing this method, we observed the heart rates and histograms shown in figure 12 and figure 13, respectively. For ecg1, the results are quite similar, with a small offset due to a few extra peaks detected using the visual method. However, the overall shapes of the datasets are identical.

In the case of ecg2, there is a strong correlation between the two datasets, but there is a slight offset at the beginning of the dataset. Nevertheless, the shapes of the datasets are also identical in this case.

While the visual method does work, it cannot be generalized for any arbitrary dataset. Its effectiveness is dependent on the specific characteristics of the ECG signals being analyzed.

Histogram is also quite identical for ecg1, and fairly similar for ecg2 dataset also, offset is due to the fact that many peaks are being missed or few noise values or S-T /P-R intervals are detected as QRS peaks.



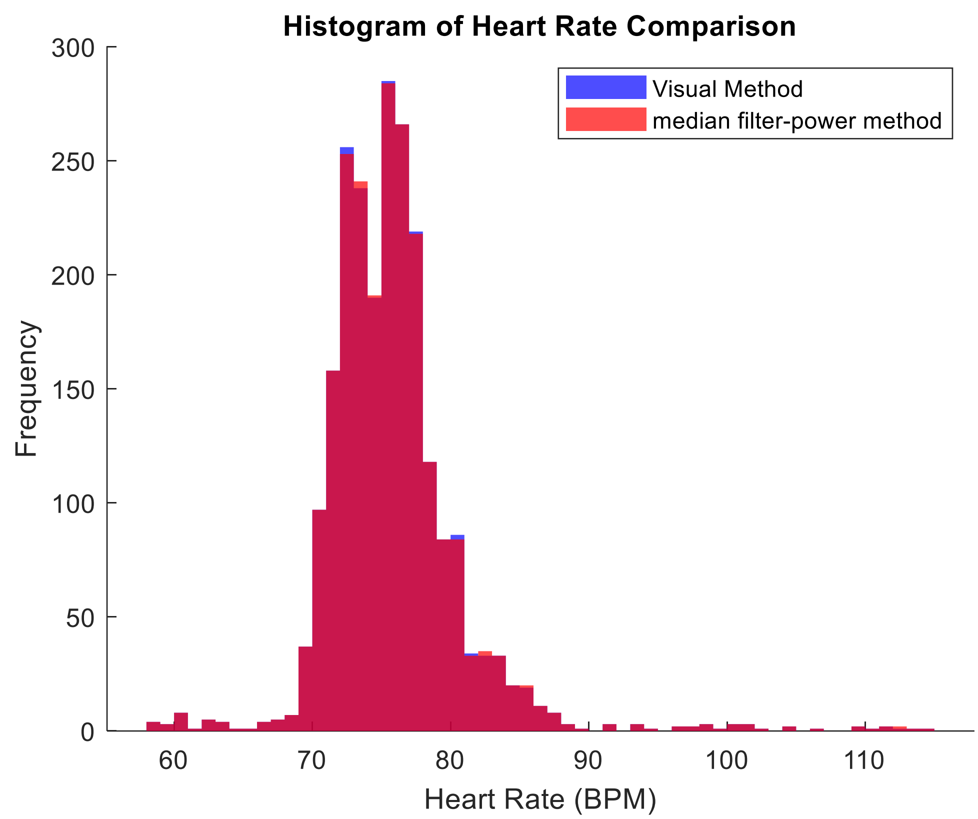
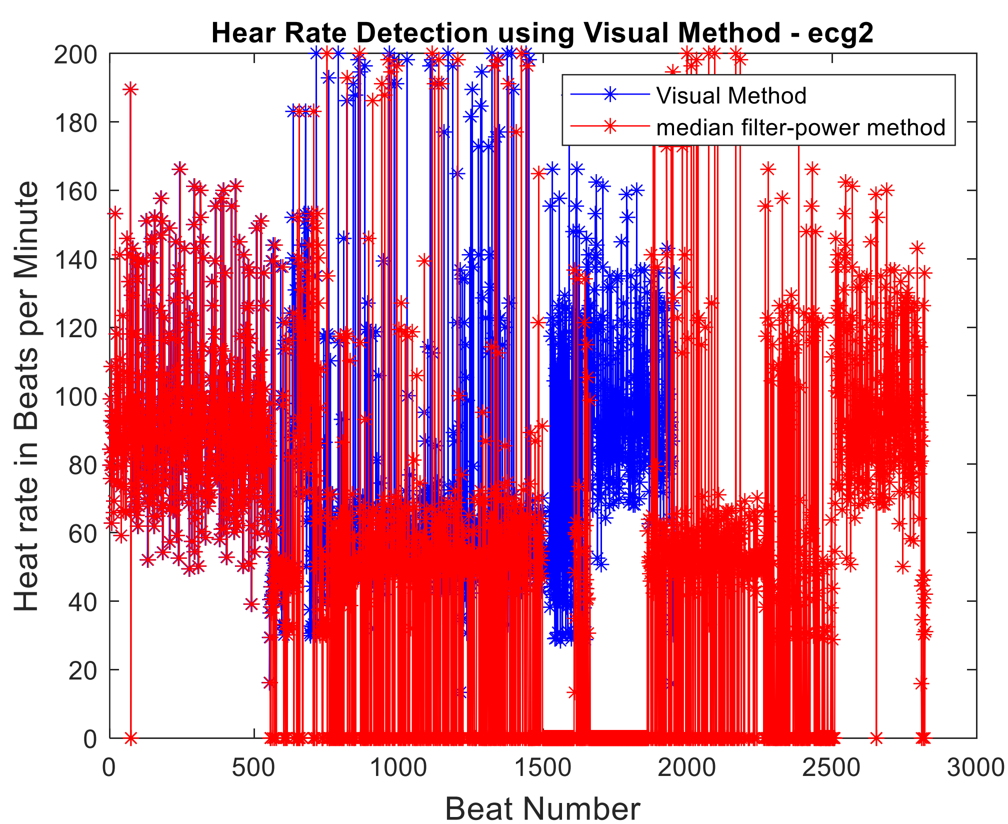



Figure 12. Comparison of BPM and histogram for ecg1



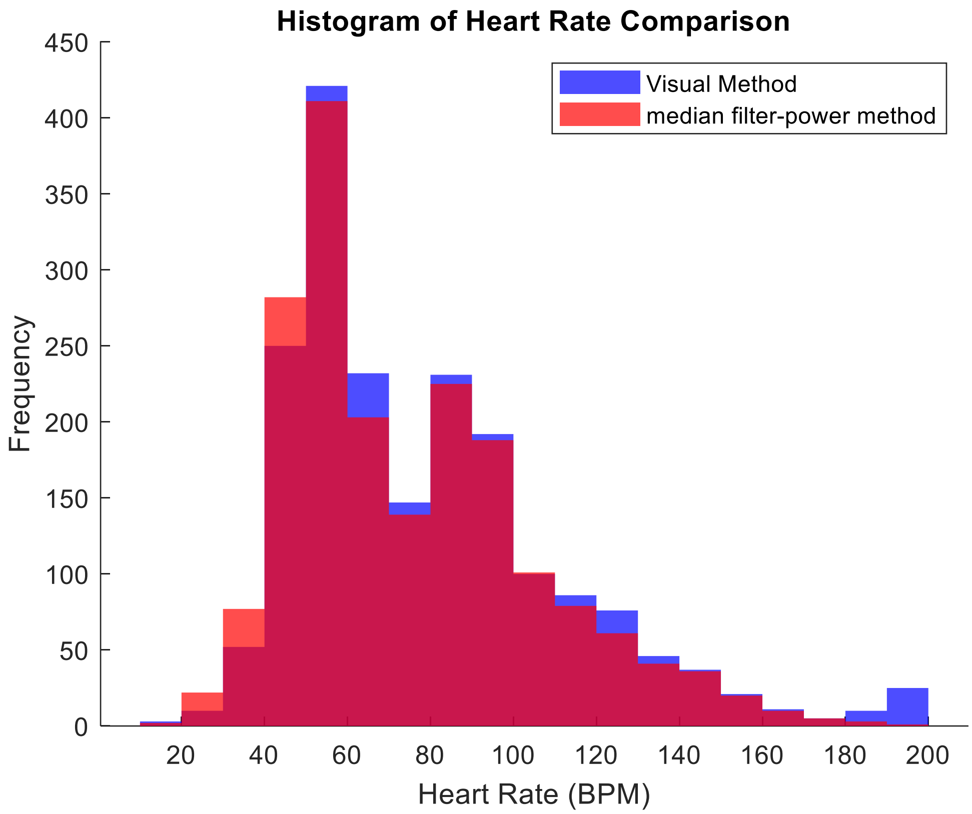



Figure 13. Comparison of BPM and histogram for ecg1

## QRS Interval Detection Algorithm:

Pinpointing the R peaks in an ECG signal often starts with visual inspection. This initial approach provides a good estimate of their location, even though some peaks might be missed. To refine the accuracy, we can delve deeper by analyzing the signal's first difference across multiple heart cycles. This reveals a distinct pattern: before an R peak, the signal typically ascends, resulting in positive values in the first difference. Conversely, the signal dips after the R peak, leading to negative values in the first difference. By leveraging this characteristic behavior, we can enhance the precision of R peak detection, ultimately contributing to a more accurate determination of the QRS interval.

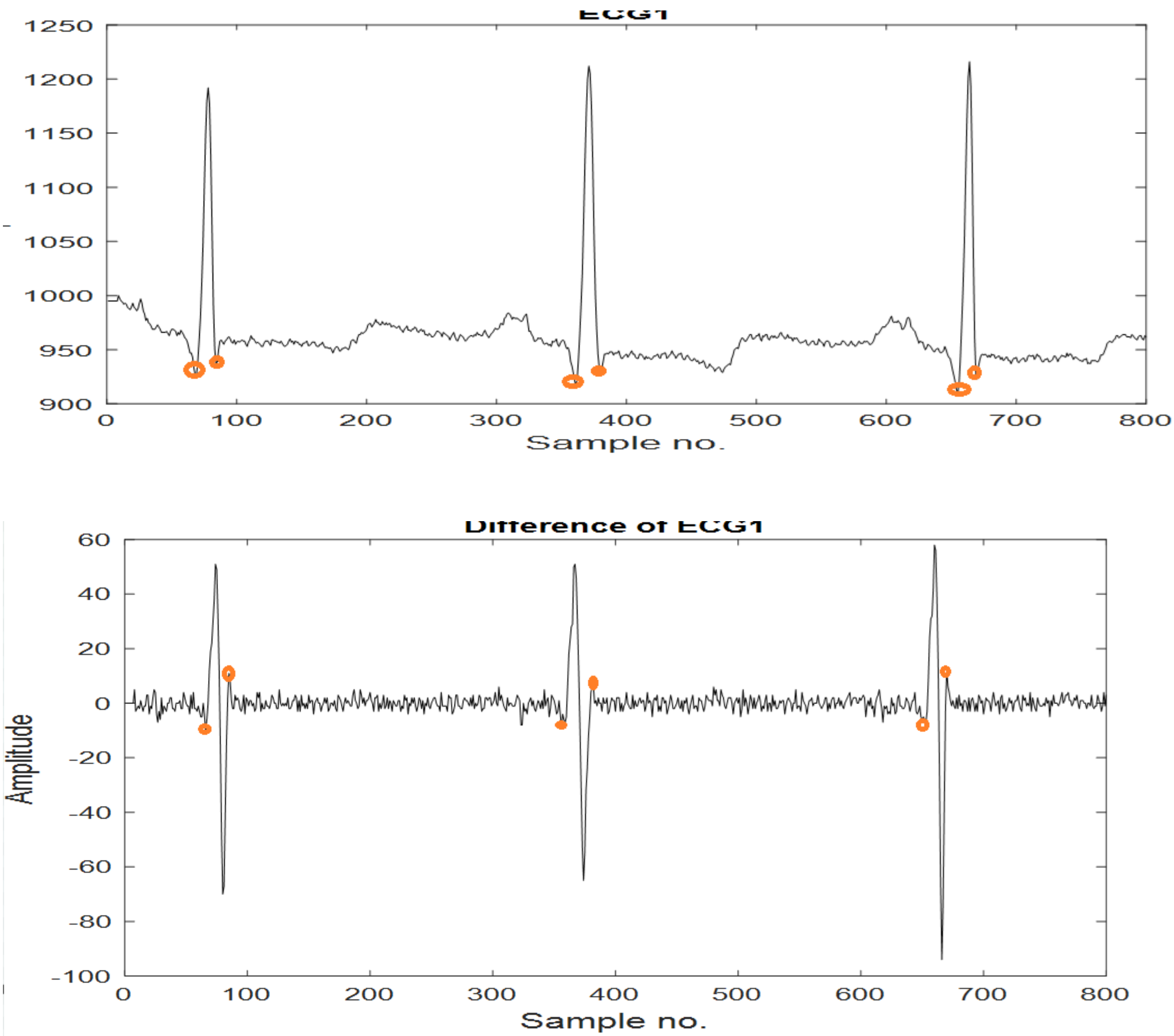



Fig 14. Algorithm description for QRS detection

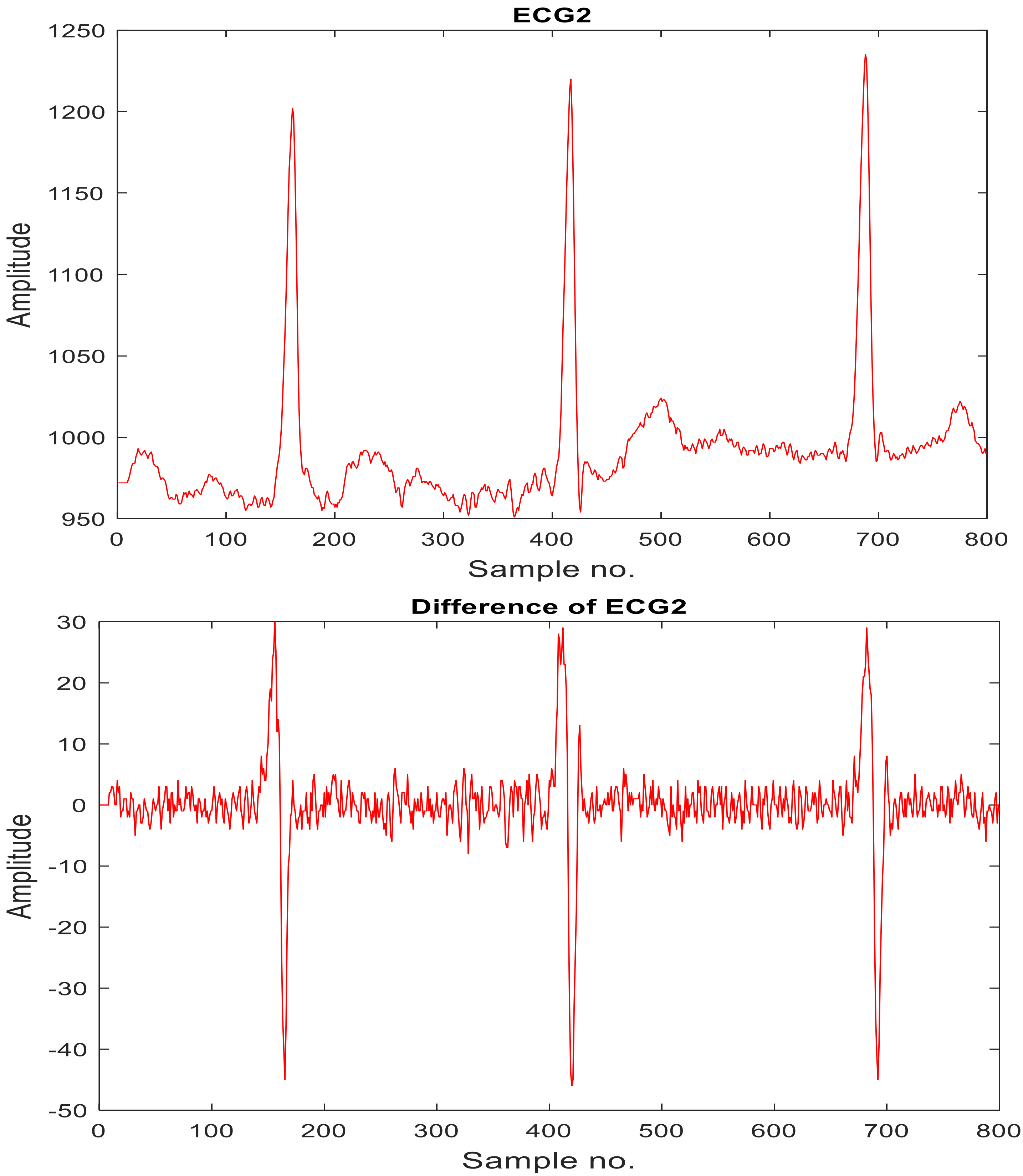



Fig 15. First difference of few samples of ecg2

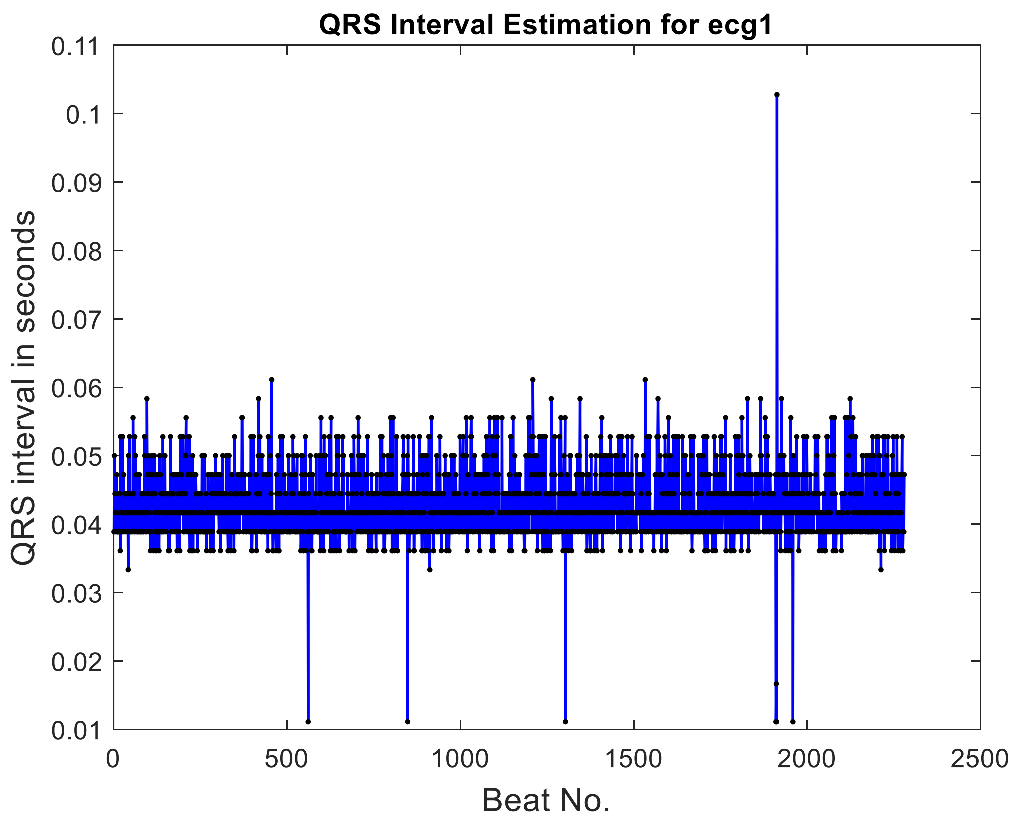
While the R peak itself might exhibit slight fluctuations in the first difference, its surrounding points reveal a crucial pattern for identifying the QRS interval. As the QRS complex unfolds after the R peak, the first difference consistently transitions to negative values, reflecting the signal's downward slope. This negative phase persists until the QRS complex concludes, at which point the first difference returns to positive values, indicating an upward slope.

Leveraging this characteristic behavior, we can pinpoint the QRS interval. Starting from the R peak, we analyze a window of data points around it. We iterate until encountering negative values to the right and positive values to the left of the peak. This window size, denoted as 'm', represents the QRS interval duration. This method effectively extracts the QRS intervals from the ECG signal, providing valuable insights into the ventricular depolarization process.

We then add the total number of samples, denoted as 'n'. The QRS interval is then calculated as:

$$QRS = \frac{1}{f_s} \times \text{n}$$

Using this method, we calculate and plot the QRS intervals for both signals in Figure 16.



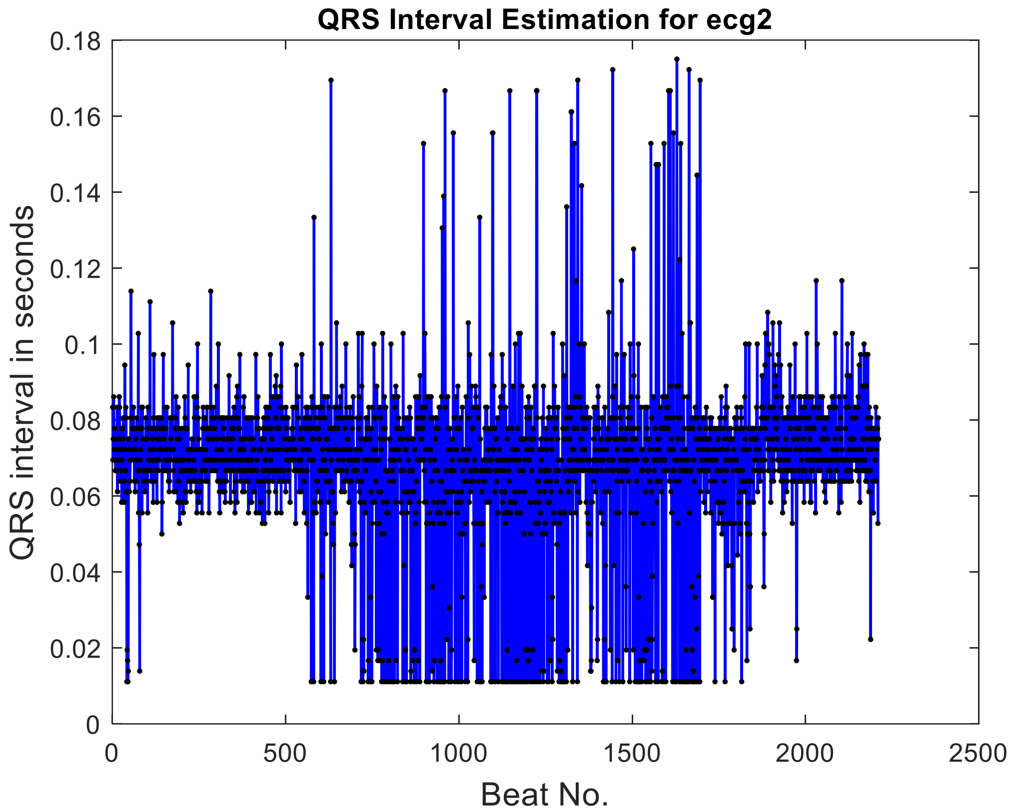



Fig 16. QRS Estimated beat by beat for ecg1 and ecg2

In the ECG signal of ecg1, the QRS intervals appear to be relatively uniform, except for 2 discontinuities. These discontinuities could be attributed to incorrect index detection, where the algorithm is counting the derivative of noise instead of the QRS complex.

On the other hand, in the ECG signal of ecg2, there is considerable abnormality, with values fluctuating frequently. Many beats exhibit either too high or too low values, indicating potential issues with signal quality or detection accuracy.

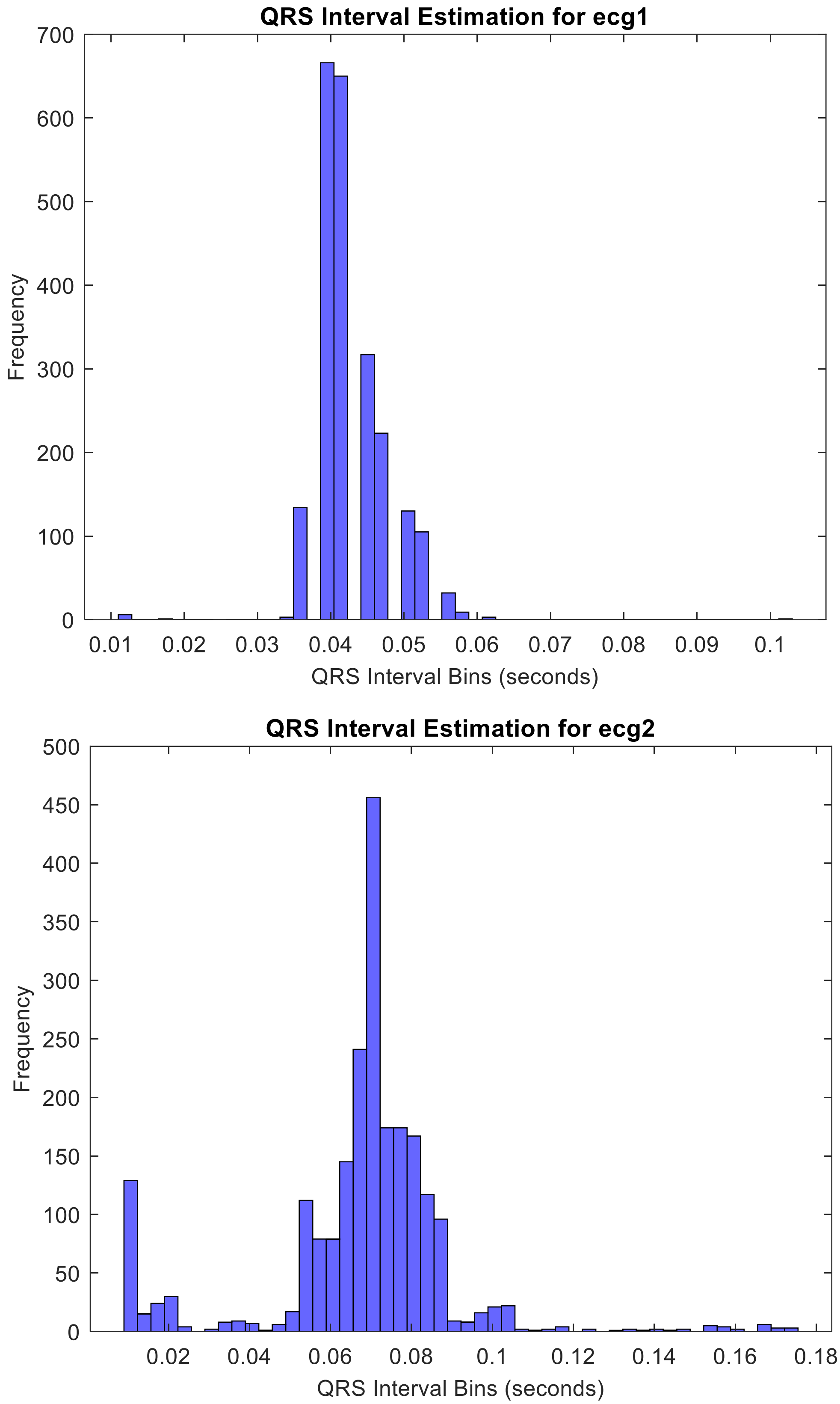



Fig 17. Histogram of QRS for ecg1 and ecg2

**References**


1. Dohare, Ashok Kumar, Vinod Kumar, and Ritesh Kumar. "An efficient new method for the detection of QRS in electrocardiogram." Computers & Electrical Engineering 40.5 (2014): 1717-1730.
2. Deboleena Sadhukhana, Madhuchhanda Mitra,“ R-peak detection algorithm for ECG using double difference and RR interval processing ”
3. https://in.mathworks.com/matlabcentral/fileexchange/10858-ecg-simulation-using-matlab