EE386 Digital Signal Processing Lab	**Aug-Dec 2023**

EndTerm Report

Review of noise removal techniques in ECG signals	**Group-10**

1 Aim

The aim of this project is to reproduce the results given by the paper [1]. In this report, we have covered three methods (1,3 and 6) of this paper. The aim of them are as follows:

- To do ECG denoising using EMD based models.
- To denoise given ECG signal using wavelet transform[2].
- To develop a Hybrid model for ECG signal denoising in order to enhance the signal quality.

2 Introduction and Literature Survey

Method 1

Empirical Mode Decomposition (EMD) is a signal processing technique that can be used for ECG signal denoising. EMD-based models aim to decompose the ECG signal into its intrinsic mode functions (IMFs) and then selectively filter out noise from these IMFs. Here's how EMD-based models for ECG signal denoising typically work:

- EMD Decomposition: The ECG signal is decomposed into a set of IMFs using the EMD technique. EMD is a data-driven method that iteratively extracts oscillatory components of different frequencies from the signal.
- IMF Selection[3]: After decomposition, the IMFs are ranked based on their frequency content and energy. IMFs with a high signal-to-noise ratio (SNR) are usually retained, while those with a low SNR, which may contain noise, are discarded.
- Noise Filtering: Various filtering techniques can be applied to the retained IMFs to further reduce noise. Common filtering methods include wavelet denoising, median filtering, or adaptive filtering.
- Reconstruction: After filtering, the denoised IMFs are reconstructed to obtain the denoised ECG signal. This can be done by summing the selected and filtered IMFs. Performance

Evaluation: The performance of the EMD-based denoising model is evaluated using metrics like Signal-to-Noise Ratio (SNR), Root Mean Square Error (RMSE), or other relevant measures. Cross-validation or separate testing data can be used to assess the model's effectiveness.

- Adaptation and Optimization: The selection of IMFs and the choice of filtering methods can be adapted and optimised based on the specific characteristics of the ECG signal and the noise present.

Method 3

Many studies in the field of ECG signal processing have employed wavelet-based denoising methods due to their effectiveness in preserving important features while removing noise. ECG signals are susceptible to various sources of noise. For instance, power line interference originating from electrical grids can introduce high-frequency noise. EMG noise results from muscle activity, and baseline wander noise can distort the baseline of the ECG. Additionally, colored noise and instrumentation noise can further complicate the analysis of ECG signals.

Wavelet theory has emerged as a potent tool for signal denoising, particularly when various thresholding approaches such as Minmax, Universal, and Level-Dependent methods are included. These algorithms try to establish a compromise between noise reduction and signal retention. Because of its durability, the Minmax thresholding approach successfully reduces noise while keeping signal features, making it a popular choice in denoising applications. Similarly, the Universal thresholding approach displays versatility across a wide range of signal types, demonstrating its capacity to preserve signal purity while decreasing noise levels. Furthermore, the Level-Dependent Thresholding technique is useful in adjusting to changing noise environments and signal properties, guaranteeing efficient denoising in a variety of settings.

In addition to these thresholding techniques, soft and hard thresholding methods play a crucial role in the denoising process. Soft thresholding, which involves shrinking small coefficients towards zero, effectively removes noise while preserving signal features. On the other hand, hard thresholding, which sets small coefficients to zero directly, efficiently eliminates noise but may lead to some loss of signal information. Understanding the trade-offs between soft and hard thresholding is essential in optimizing the denoising process to meet specific signal processing requirements.

The Signal-to-Noise Ratio (SNR) assessment, which measures the ratio of the intended signal power to the noise power, is frequently used to evaluate the quality of denoising algorithms. This assessment gives critical insights into the efficacy of denoising approaches, allowing researchers and practitioners to make educated judgements about thresholding strategies and their effects on signal quality. It is feasible to acquire a full grasp of denoising performance and optimize the signal processing workflow for superior outcomes by examining the SNR ratio with the deployment of various thresholding approaches.

The wavelet transform is particularly well-suited for analyzing ECG signals. It allows for the decomposition of signals into different frequency components at multiple scales, making it possible to isolate noise from the ECG's essential information

The standard MIT-BIH arrhythmia data from PhysioNet is a commonly used benchmark dataset in ECG denoising studies. Its widespread use facilitates the comparison of different denoising techniques and the evaluation of their performance

Method 6

In this suggested hybrid model, we have tried combining EMD technique (Empirical Mode Decomposition) that rejects the initial EMFs and then apply wavelet-based approach along with the concept of adaptive switching mean filter (ASMF) to denoise ECG signals and enhance the overall signal quality and performance.

Even after the application of EMD technique and wavelet-based approach numerous types of noise and artefacts still exist in the ECG signal which produces low quality signal data. Hence below mentioned method is incorporated.

- Adaptive switching mean filter: This is a signal processing technique used for noise reduction in ECG which is designed to adaptively switch between the two filters looking at signal characteristics. It helps in smoothing out high frequency components. After EMD based denoising some noises still exist in the reconstructed signal. Hence ASMF is applied for further enhancement of signal quality whose basic principle is the similarities of the neighbourhood samples of a signal.

- R-peak position information: The R-peak information corresponds to the highest point of each QRS complex and contains important information about the electrical activity of the heart and hence can't be lost during processing. Hence necessary steps are taken to avoid the loss of r-peak using r-peak detection algorithm.

3 Methodology and Algorithms

Method 1 [4]

- Input:
  Begin with the noisy ECG signal as the input, which contains the desired cardiac information along with unwanted noise.

- Sifting Process:
  1. Identify Extrema (Maxima and Minima): Locate the peaks (maxima) and troughs (minima) in the noisy ECG signal. These points are vital for understanding the underlying

oscillatory behavior of the signal.
2. Interpolate Upper and Lower Envelopes: Use cubic spline interpolation to create smooth curves that join the identified maxima and minima, forming upper and lower envelopes. These envelopes help define the dominant oscillatory patterns in the signal.
3. Calculate the Mean Envelope: Compute the mean of the upper and lower envelopes to represent the central tendency of the oscillations in the signal.
4. Extract the IMF (Intrinsic Mode Function): Subtract the mean envelope from the noisy ECG signal. This process helps to isolate one of the intrinsic oscillatory components of the signal, known as the IMF.
5. Update the Residue Signal: Modify the noisy ECG signal by subtracting the extracted IMF. This updated signal (residue) now contains the remaining components and noise.

- Termination Criterion:
  Check if the residue signal is either a constant or exhibits a monotonic slope, or if it is a function with only one extremum. If this condition is met, the algorithm terminates, indicating that further extraction of IMFs is not necessary.

- Reconstruction:
  Reconstruct the denoised ECG signal by adding together all the extracted IMFs. This results in a denoised signal that has been cleaned of unwanted noise.

Method 3

The denoising process can be summarized in the following algorithm:

Step 1: Selection of Wavelet Function :

Choose a suitable wavelet function based on the specific application and properties of the analysed signal. Commonly used wavelets include Daubechies, Haar, Coiflet, and Symlet, each with different properties and characteristics. We have used the Daubechies and Symlet waves to perform our experiment.

Step 2: Apply Discrete Wavelet Transform (DWT):

Discrete Wavelet Transform is a mathematical technique that decomposes a signal into different frequency components at various scales. In ECG denoising, the noisy ECG signal is subjected to DWT. This involves breaking down the original ECG signal into wavelet coefficients at different levels, called sub-bands. These coefficients represent the signal's information at different frequency scales, with the highest scales capturing fine details (usually noise) and the lower scales capturing more global features.

Step 3: Decomposition :

Decompose the signal into approximation coefficients and detail coefficients through a process known as multiresolution analysis. This involves filtering the signal at different scales using high-pass and low-pass filters, which separates the signal into different frequency bands.To calculate the threshold frequency we have used Universal,MinMax and Level Dependent methods.

- Universal Method: The universal method in wavelet transformation involves using a single wavelet function that can efficiently approximate a wide range of signals. With this approach, different signal types will not require special modifications or adaptations since a universal wavelet will be discovered that can accurately represent them all.
- MinMax Method: The Minmax method in wavelet transformation focuses on optimizing the approximation properties of the wavelet function, aiming to minimize the maximum error in representing different classes of signals. This method involves selecting a wavelet that minimizes the maximum error across different types of signals.
- Level Dependant Method: In the level-dependent method, the wavelet transformation is applied with a specific level of decomposition, which determines the number of times the signal is decomposed. The choice of decomposition level depends on the application's specific requirements and the desired resolution of the signal analysis.

Step 4: Perform Soft or Hard Thresholding:

The next step involves applying the chosen thresholding method (either soft or hard thresholding) to the wavelet coefficients obtained in Step 1. This process is performed at each level of the wavelet decomposition. Here is how each type of thresholding works:

- Soft Thresholding: In soft thresholding, wavelet coefficients whose magnitudes exceed the threshold value ($|x| >$ T) are retained, while those with magnitudes below the threshold are set to zero. Soft thresholding tends to produce smoother results because it reduces the amplitudes of significant coefficients without eliminating them.
- Hard Thresholding: Hard thresholding retains coefficients with magnitudes greater than the threshold value ($|x| >$ T) and sets all others to zero. This approach is more aggressive in eliminating noise because it completely discards coefficients that do not meet the threshold criterion.

Step 5: Reconstruct the Denoised ECG Signal:

After applying the thresholding method in Step 3, the modified wavelet coefficients are used to reconstruct the denoised ECG signal. This reconstruction is achieved using the inverse Discrete Wavelet Transform (IDWT). The IDWT combines the thresholded coefficients from different scales to recreate the denoised signal, emphasizing the preserved information while reducing the noise.

Step 6: Evaluate Performance in Terms of Signal-to-Noise Ratio (SNR):

To assess the effectiveness of the denoising method, it is crucial to evaluate its performance quantitatively. One standard metric for this purpose is the signal-to-noise ratio (SNR). SNR measures the ratio of the signal's power to the power of the residual noise. A higher SNR indicates a better denoising outcome, as the signal is more dominant than the remaining noise.

In summary, this denoising algorithm leverages Discrete Wavelet Transform and thresholding techniques to enhance the quality of ECG signals. The choice of thresholding method and threshold value and the evaluation of the denoising performance using SNR are critical components of this process, ensuring that crucial cardiac information is preserved while noise is effectively reduced.

Method 6

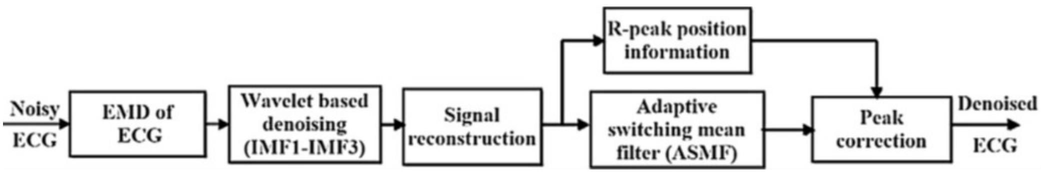


Figure 1: Hybrid Model

6.1 EMD and wavelet thresholding:

The ECG dataset is downloaded MIT-BIH arrhythmia database and white gaussian noises with signal to noise ratio 10dB are added to get the ECG noised signal. The duration of the signal taken is 10 seconds. The noised signal is used for empirical mode decomposition where it is decomposed to set of oscillatory functions called intrinsic mode functions (IMF) as mentioned in methodology 1. The lower order IMFs (IMF1-IMF3) contain very high frequency interference and QRS complexes. Thus, these IMFs cannot be rejected in order to preserve QRS complexes. Hence after extraction of IMFs, these lower order IMFs are denoised using a wavelet soft thresholding technique. The wavelet denoised IMFs are then added back along with the remaining IMFs and the residue signal. XwECG[n] is the denoised reconstructed signal after wavelet thresholding. C'l,ECG[n] denotes the wavelet denoised IMFs. Cl,ECG[n] is the noisy IMF.

$$X^{w}_{ECG}[n] = \sum_{l=1}^{3} C'_{l,\,ECG[n]} + \sum_{l=4}^{L-1} C_{l,\,ECG[n]} + r_{L}[n]$$

6.2 R-peak detection algorithm [5]**:**

Here we have used the Pan-Tompkins QRS detection algorithm. This is applied to the reconstructed ECG signal to detect the R-peaks. These R-peaks are then added back to the denoised signals to ensure no loss of information before applying the ASMF filter.

Pan-Tompkin's algorithm utilises the amplitude, slope and width of an integrated window. The algorithm consists of two stages pre-processing and decision. In first stage the noise removal, signal smoothing, and width and QRS slope increasing is done. Then the thresholds are used to only consider the signal peaks and eliminate the noise peaks in the nest stage. The steps include:

1. Bandpass filtering: This reduces the influence of noise while preserving the QRS complex. The ECG signal is passed through a bandpass filter to isolate frequency range of interest.

2. Differentiation: After filtering, the signal is differentiated and low frequency P and T waves are suppressed in the derivative process to get high frequency signals in the complex.

3. Squaring: The obtained signal is squared to get sharp, and all positive value. Higher amplitudes are further enhanced while attenuating other parts of the signal. Moving window integration (MWI): also known as the moving average is applied in order to smoothen the signal and emphasise on the overall energy of the QRS complex.

4. Decision: This is performed to decide whether or not the result of MWI is a QRS complex with the help of thresholds. An adaptive threshold is calculated based on mean and SD of the integral signal to determine the match with QRS complex. The peaks that surpass the adaptive threshold is considered as potential R-peaks. However necessary steps are taken to avoid the detection of noise and T waves as R peaks.

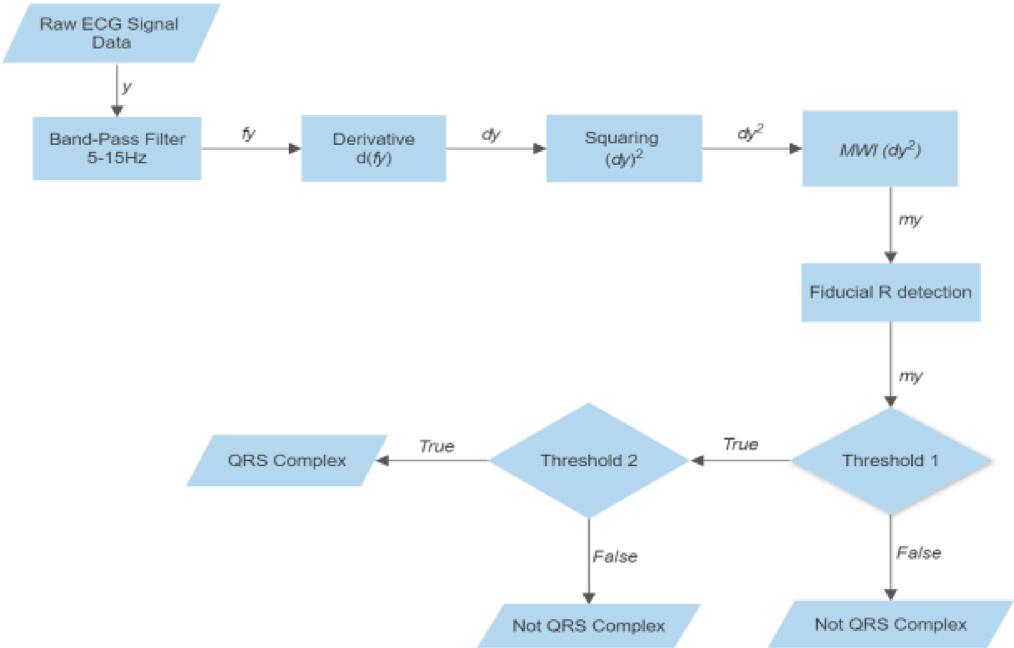


Figure 2: Pan-Tompkin's algorithm

6.3 Adaptive switching mean filter (ASMF) algorithm: Even after EMD and wavelet denoising some noises still exist in the reconstructed signal. these noises are visible in the lower components in QRS complexes. Thus, the wavelet denoised signal is further denoised in order to enhance the signal quality and get rid of remaining noises. The adaptive switching mean filtering approach operates on the principle that neighbouring samples in a signal should exhibit similarity.
1) A fixed-length window is selected and during each iteration, the centre of this window is placed on a test ECG sample.
2) A threshold value is determined by calculating the standard deviation of the samples that are present within this window.
3) If the difference between the test ECG sample and the mean value of the samples within this window crosses the threshold limit, the test ECG sample is considered as a corrupted sample.
4) The corrupted sample's value is then updated to match the mean value of the surrounding samples within the window.
The thresholding selecting parameter which determines the limit of the threshold value is empirically taken 0.5 and a window of length 10 samples is chosen.

6.4 Peak correction algorithm: However, the R-peaks in the ECG signals which carry vital information regarding the function of heart are attenuated due to the ASMF operation. Hence, the recovery of these peaks is an essential of denoising. The approximate R-peak locations are obtained from the detection algorithms. In this method the peaks are corrected by utilizing the position information of R-peaks according to the peak correction algorithm. XECGp[n] is the ASMF processed signal obtained after ASMF filter is applied to XwECG[n]. XECGp[n] is the peak corrected signal. R-peak sample position nR is obtained. For the samples in the range nR-10 to nR+10 the XECGp[n] is equal to XwECG[n]. For all the other values of nR , XECGp[n] is equal to XECGp[n]. The final peak corrected signal is obtained by carried out the algorithm for all value of nR.

4 Results, Discussions and Comparison between different methods

The dataset used by us is `https://physionet.org/content/mitdb/1.0.0/` and the tool box is WFDB Toolbox : `https://archive.physionet.org/physiotools/matlab/wfdb-app-matlab/`.

We took one record from the dataset and did the coding for 10-15 seconds part to get a clear picture about the changes happening. We added White Gaussian noise to the signal as the dataset had no noise. White Gaussian noise (WGN) is a specific type of random noise commonly used in signal processing and communication systems for various purposes, including testing and simulation.

Method 1

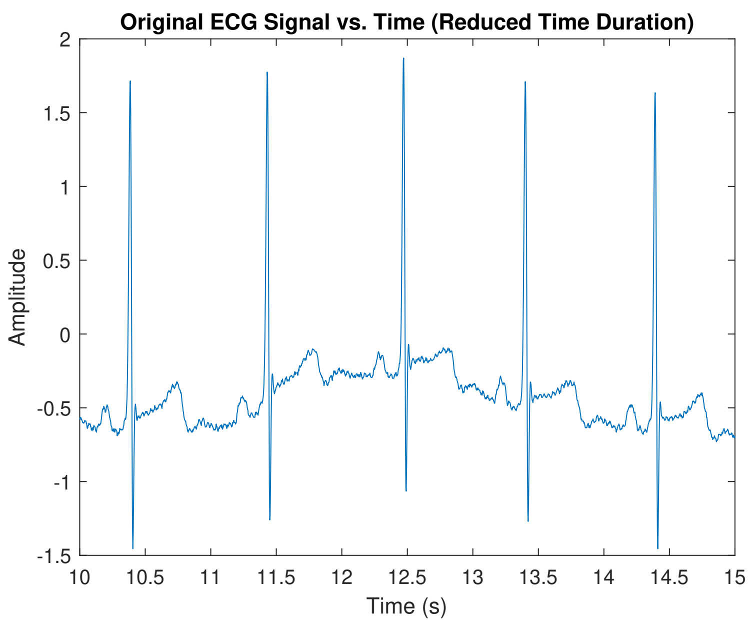


Figure 3: Original Signal from Dataset

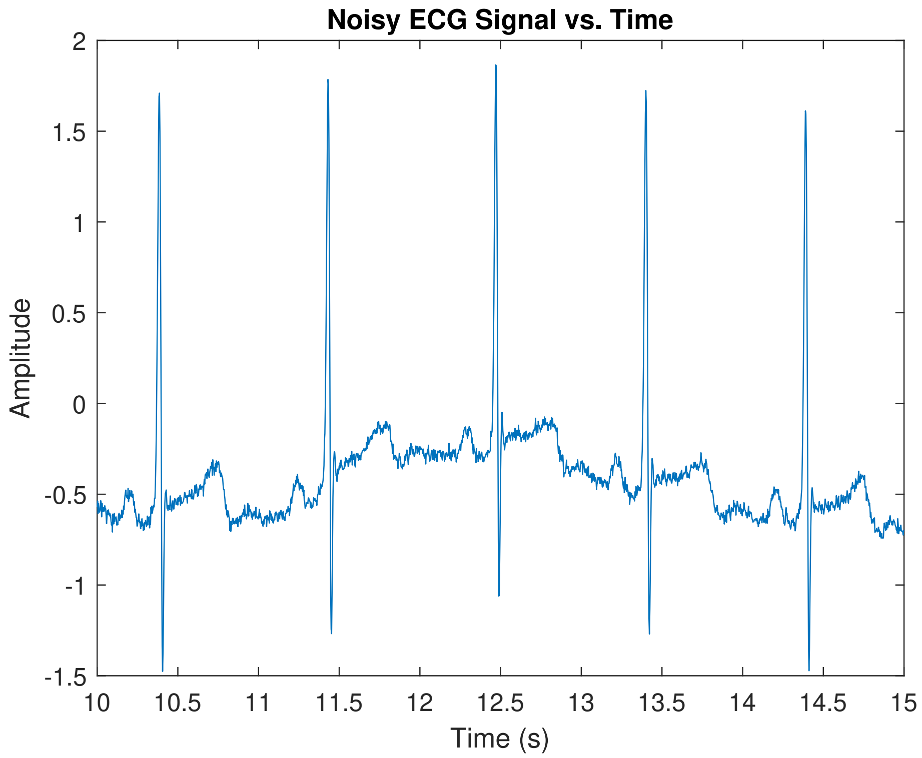
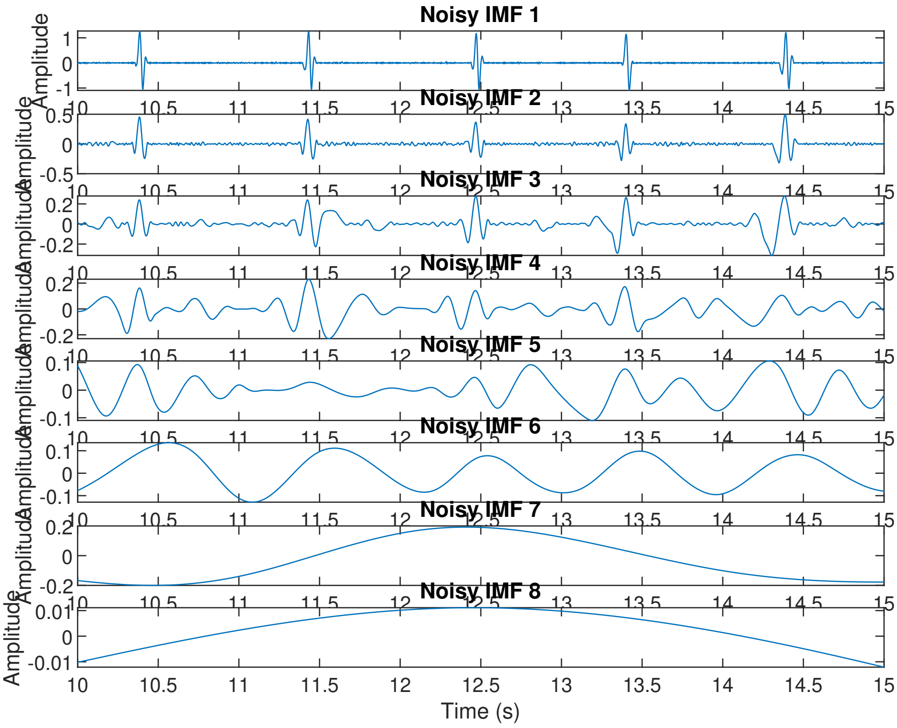
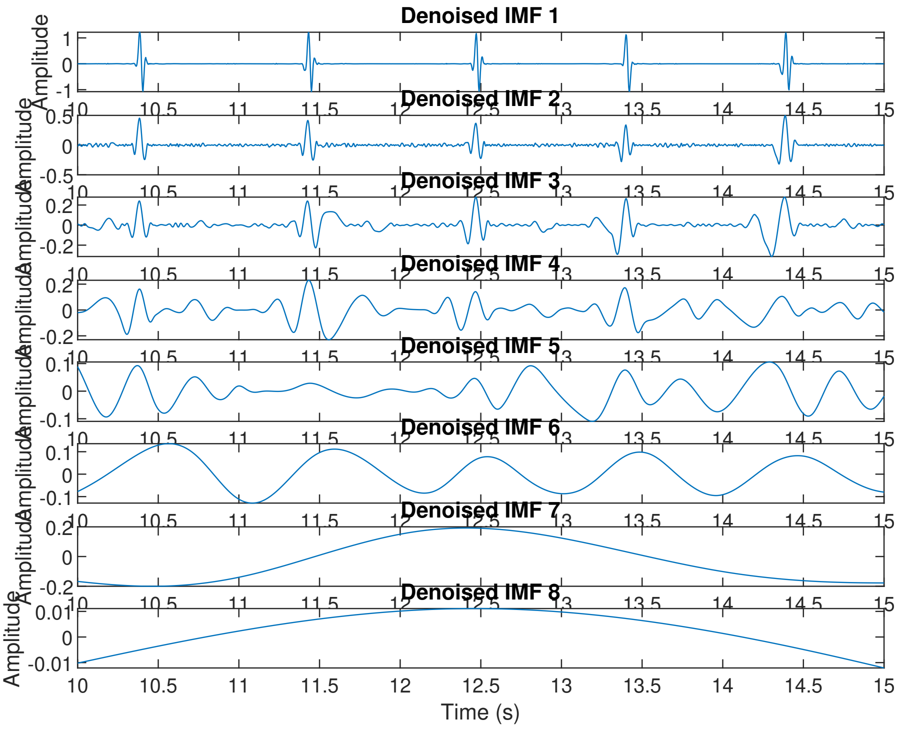


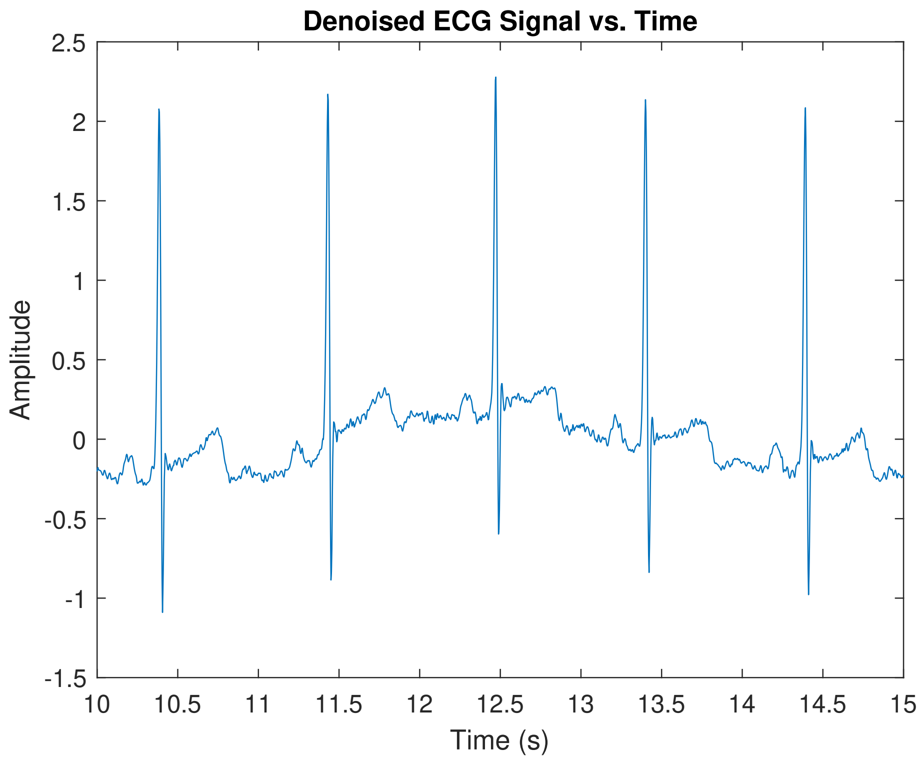
Figure 4: Noisy Signal

The sifting process is an iterative refinement technique. The goal is to iteratively extract and refine the highest-frequency components of the signal and gradually improve their quality. Each iteration focuses on one IMF at a time, reducing the contribution of lower-frequency components. The residue, which initially contained the entire signal, becomes the residual signal after each iteration. It represents the lower-frequency components that have been removed from the signal by subtracting the IMFs extracted in previous iterations.





The final denoised signal is obtained by summing all the updated IMFs and the residual signal. This reconstructed signal aims to represent the original signal with improved quality, as the noise and lower-frequency interference have been reduced.

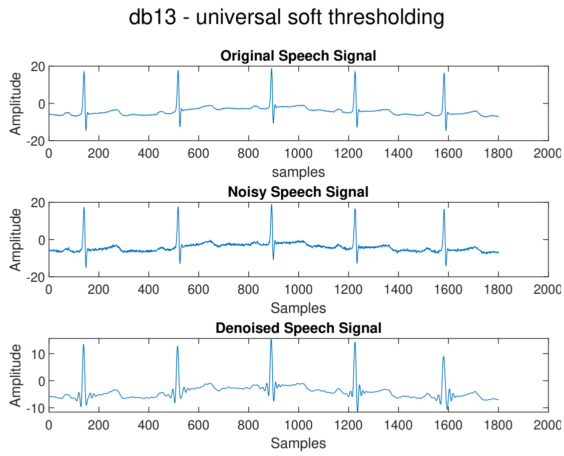


As you can see the denoised signal is almost same as the original signal .

Method 3

The choice of wavelet mother function, thresholding technique, and type of thresholding directly impact the signal-to-noise ratio (SNR) of the denoised signal. In general:

- A well-chosen wavelet mother function can help effectively separate signal from noise and preserve signal features, which can improve SNR.
- The thresholding technique used can determine how effectively noise is reduced. Level-dependent thresholding is particularly useful for preserving fine and coarse features, potentially leading to a higher SNR.
- The type of thresholding can also influence SNR. By attenuating rather than eliminating coefficients, soft thresholding may result in a higher SNR than hard thresholding in some cases.


db13 - universal soft thresholding
Original Speech Signal
Amplitude
samples
Noisy Speech Signal
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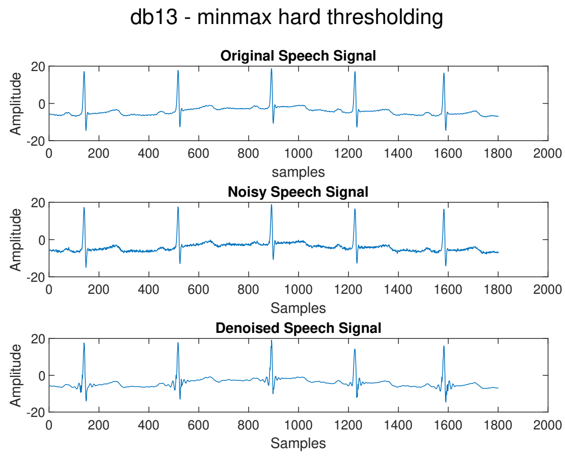
Denoised Speech Signal
Amplitude
Samples


db13 - minmax hard thresholding
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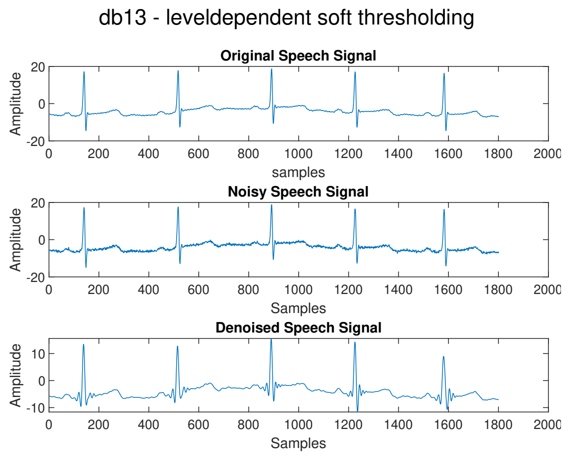
db13 - leveldependent soft thresholding
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Denoised Speech Signal
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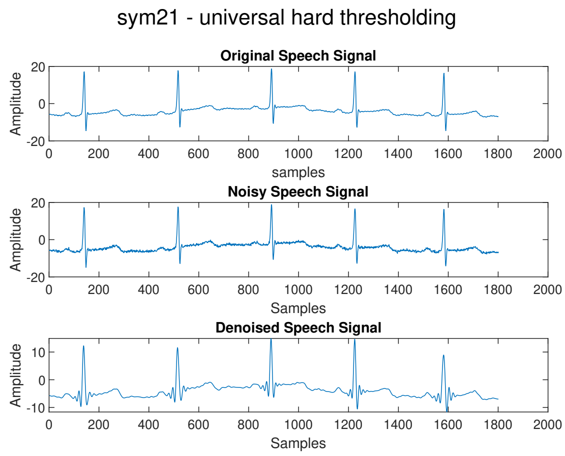
sym21 - universal hard thresholding
Original Speech Signal
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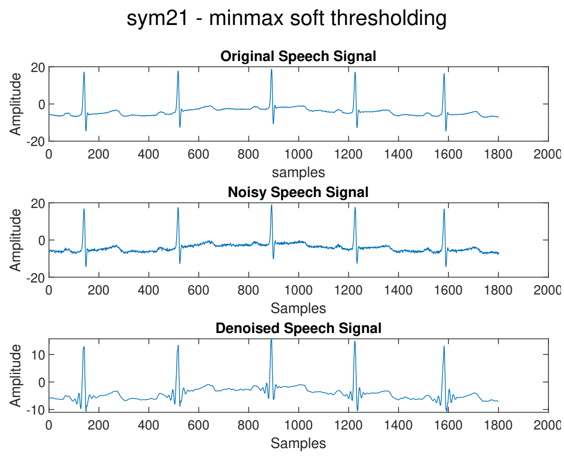
samples
Noisy Speech Signal
Amplitude
Samples
Denoised Speech Signal
Amplitude
Samples


sym21 - minmax soft thresholding
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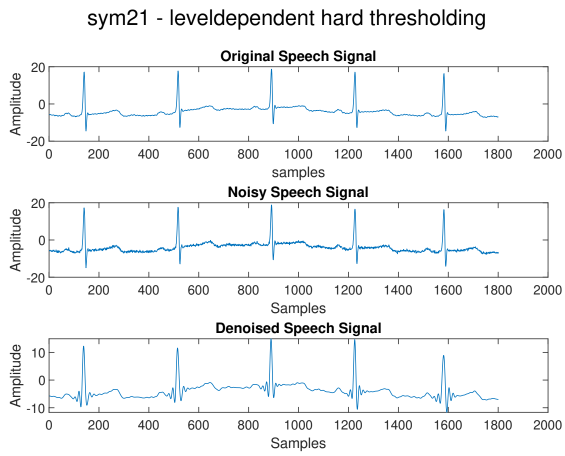
sym21 - leveldependent hard thresholding
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Method 6

The noisy ECG signal taken is given by

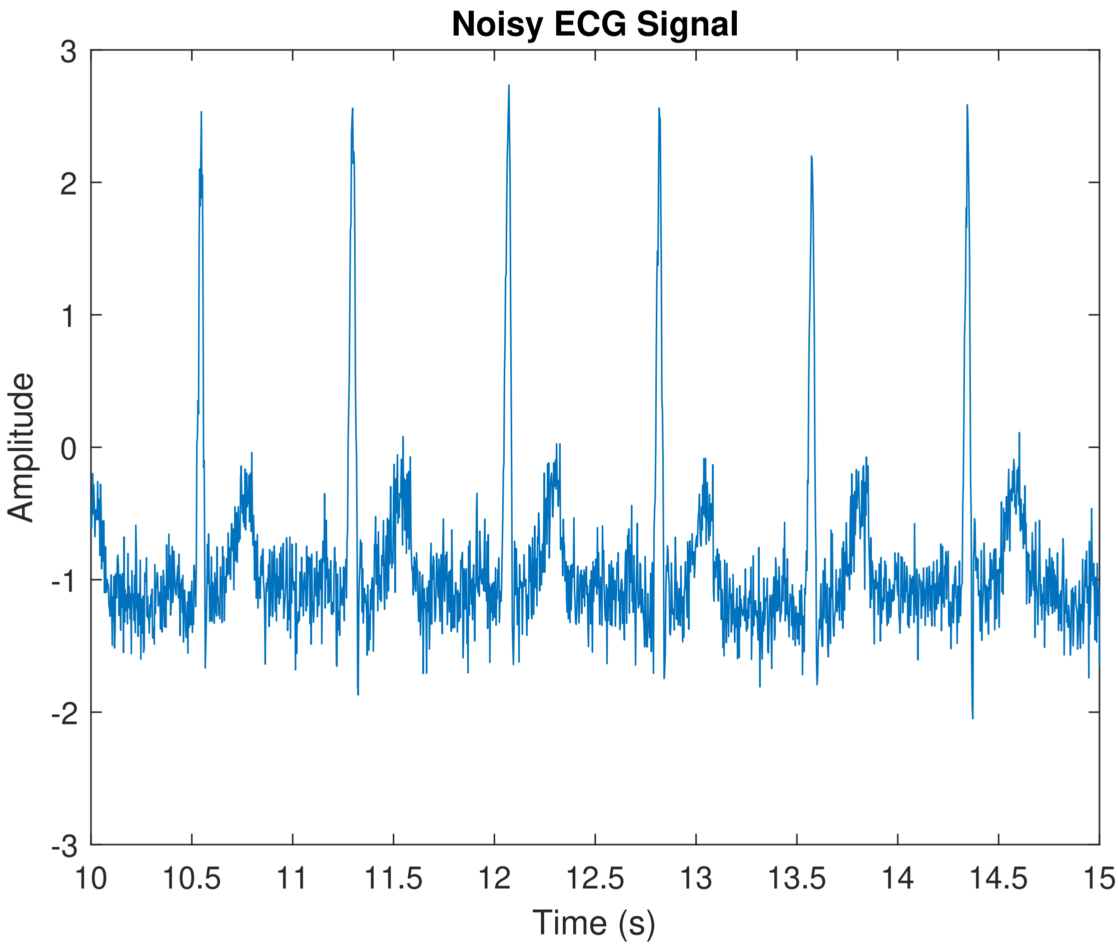

Figure 8: Plot 1

After Empirical mode decomposition the noisy IMF's obtained and the denoised IMFs after soft wavelet thresholding respectively are given by

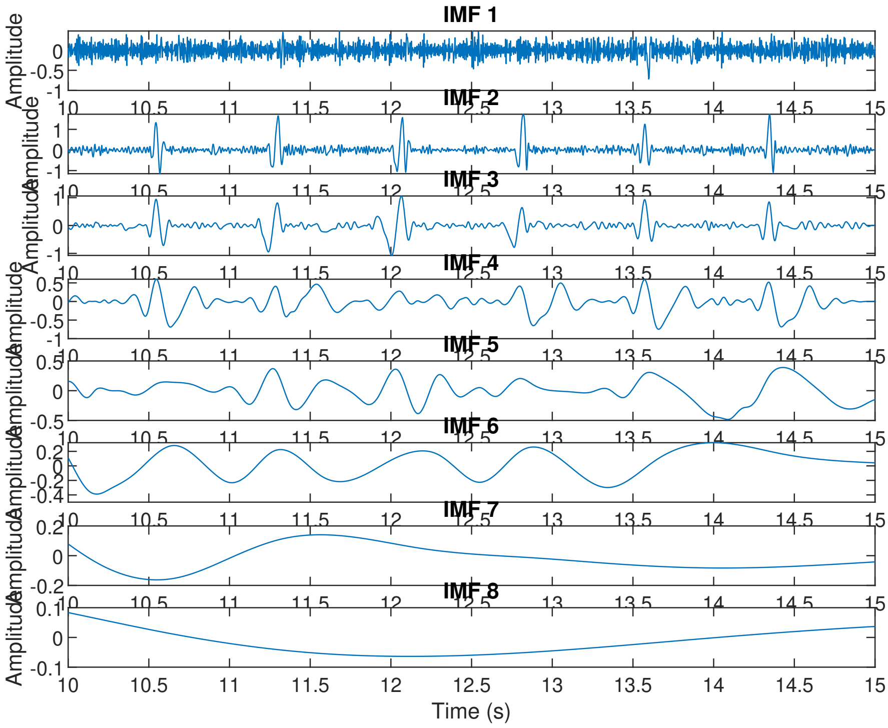

Figure 9: Plot 2

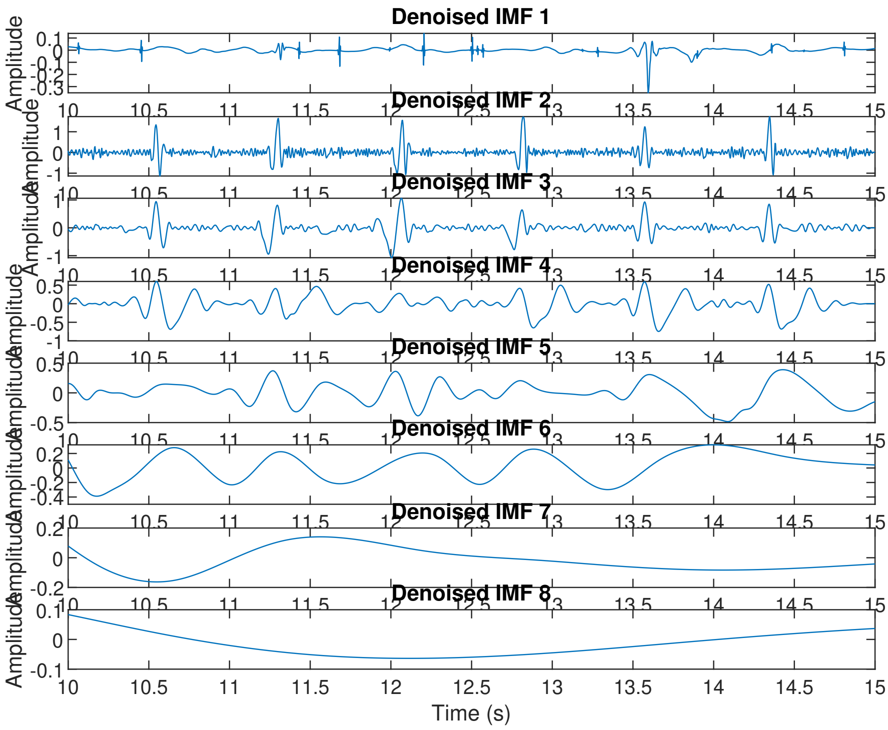

Figure 10: Plot 3

Plot 2 clearly depicts that the initial 3 IMFs have the highest noise. However, these cannot be rejected since it contains the QRS complexes. Hence it is very essential to denoise them. Remaining IMFs are not denoised and are added back to the denoised IMF1-IMF3 since they do not contain very significant noises. Plot 3 shows that the IMF1 to IMF3 are denoised. Remaining IMFs remain unaffected.

The reconstructed signal obtained after the wavelet thresholding by adding all the IMFs is given by

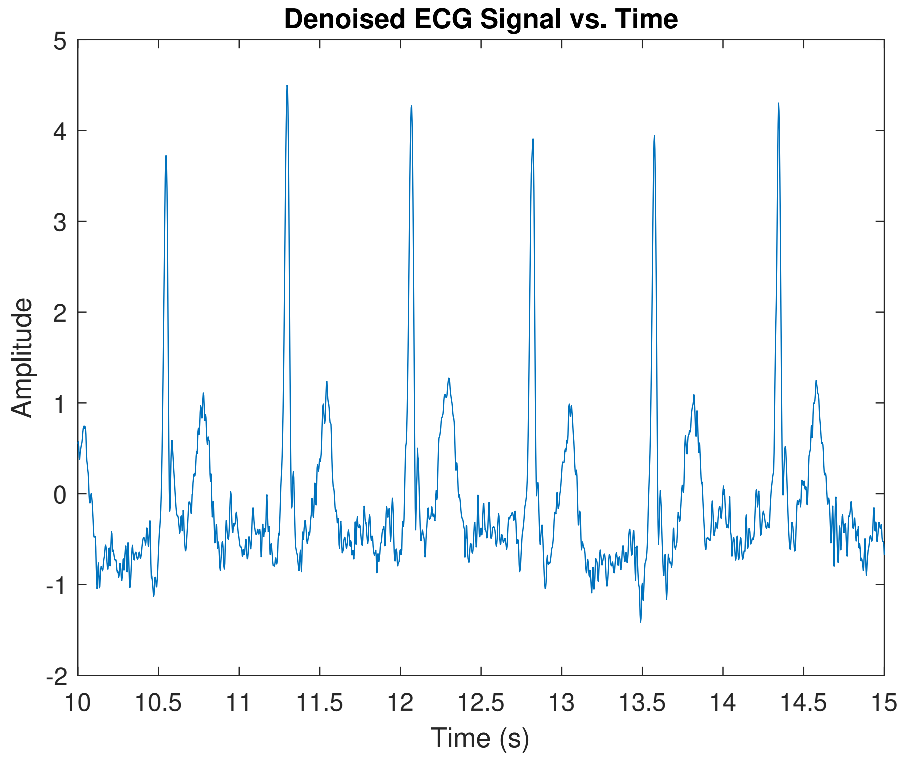

Figure 11: Plot 4

On comparison of Plot 4 and Plot 1 it is evident that most of the interference in the original signal is denoised after initial denoising. However, some noise still exists in the reconstructed signal. Hence, it is essential to use more techniques to improve the quality of the signal.

Thus the reconstructed signal is denoised using adaptive switching mean filter. QRS complex detection is done before applying ASMF as shown in Figure 5 using Pan-Tompkin's Algorithm.

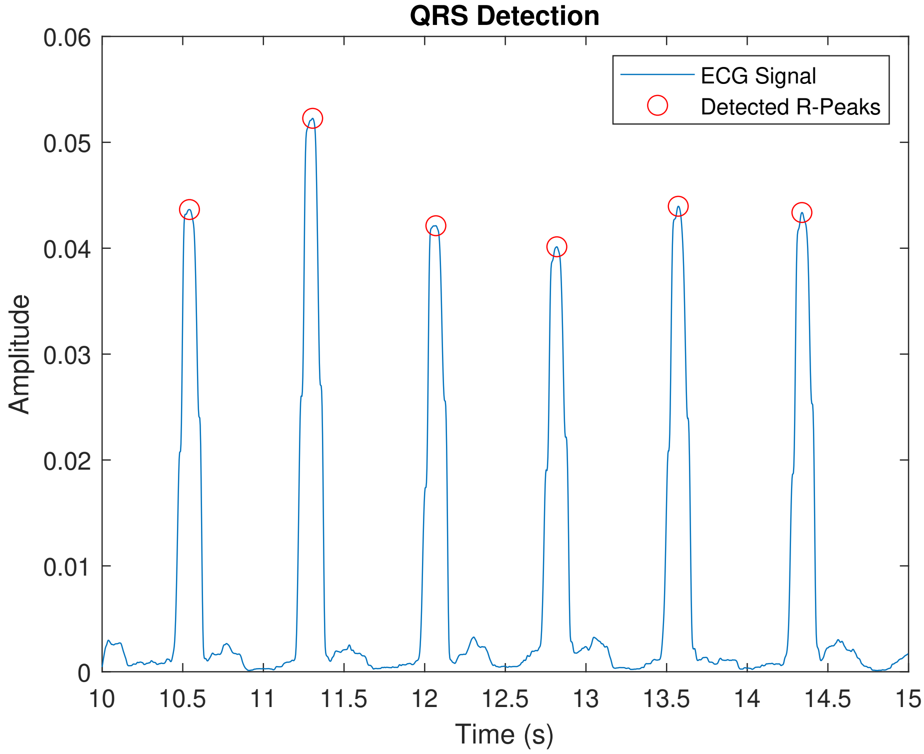

Figure 12: Plot 5

As mentioned in the methodology it is essential to exclude the indices near the R-peaks before applying the filter since these R-peaks get attenuated by ASMF filter. This is one of the major disadvantages of ASMF filter since R-peaks contain vital information pertaining to heart function. Hence thorough study of the R-peaks is made as shown. These are then added back after application of ASMF filter so that no vital information is lost.

In case the R-peaks are not excluded before application of ASMF the overall signal gets affected as shown in Plot 6

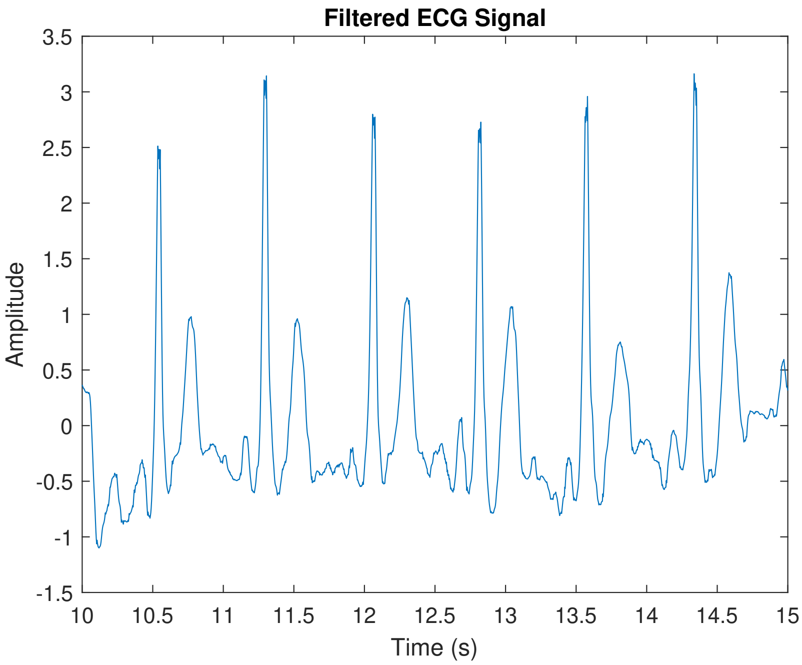

Figure 13: Plot 6

Hence the detected R-peaks are added back according to the peak correction algorithm and the peak corrected signal is obtained as shown in Plot 7. Comparison of Plot 7 and Plot 6 shows the significance of R-peaks.

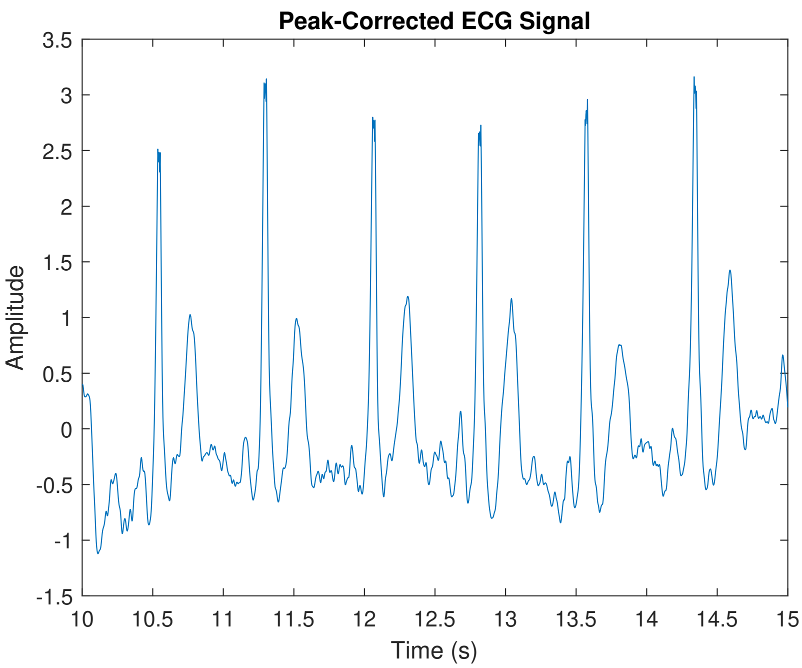

Figure 14: Plot 7

Comparison of Plot 7 and Plot 4 shows that the hybrid model further reduces the noise and proves to be more efficient than the individual techniques. The individual methodology reduces noise to a certain extent. However some noise still exists which require further examination and filtering. The Hybrid model proposed above which shows combining the Wavelet denoising after the empirical mode decomposition followed by the application of adaptive switching mean filter by carefully determining the R-peaks enhances the overall quality of the ECG signal by reducing the unwanted noises so that the signal can be used for efficient future analysis. This is only one of the proposed hybrid models which shows a significant reduction in signal to noise ratio.

Evaluation Metrix: We used Signal to Noise Ratio as evaluation metrix. In simple terms, SNR is a measure of the quality of a signal compared to the unwanted background noise present in the same environment. Think of it as a way to determine how clearly you can hear a person speaking in a noisy room. This is the performance evaluation of our methods:

Method 1 : SNR of Noisy Signal is -0.0038.
SNR of Denoised Signal is 4.1772.

Method 3: SNR of Noisy Signal is -0.0215
SNR of Denoised Signal is 3.2867.

Method 6: SNR of Noisy Signal is -0.1591.
SNR of Denoised Signal is 2.4381.

5 Contribution of each member and the Repository Link

We have formed pairs and assigned one of the three methods to each pair. Each pair has diligently conducted a comprehensive literature review, ensuring a deep understanding of the algorithms. We have now shifted towards the practical implementation phase, where we have begun coding.

- Charu Shah (2110286) and Surya Abhinay (2110525): Method 1- ECG Denoising using EMD based models.
- Dev Goti (2110289) and Prakhar Goel (2110273): Method 3- ECG Denoising using Wavelet based models.

- S V Sowndarya (2110268) and Sneha Sri Dulam (2110308): Method 6- ECG Denoising using Hybrid methods.

The codes can be found in the GitHub repository: `https://github.com/devgoti16/ECG-Denoising`.

References

[1] Ram Narayan Yadav Lalita Gupta Deepak Kumar Raghuvanshi Shubhojeet Chatterjee, Rini Smita Thakur. Review of noise removal techniques in ecg signals. *IET Signal Processing*, 2020.

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