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

MidTerm 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.

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

Thresholding methods play a crucial role in wavelet-based ECG denoising. Two primary approaches are soft and hard thresholding. Soft thresholding retains coefficients above a threshold and sets the rest to zero, while hard thresholding keeps coefficients above a threshold and sets others to zero. The choice of the threshold value is a critical factor influencing denoising performance. Wavelet denoising extends beyond ECG signal processing. It is widely used in various fields, including data mining, medical signal and image analysis (e.g., ECG, CT scans), and radio astronomy image analysis

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.

Figure 1: Methodology of EMD based models

Method 3

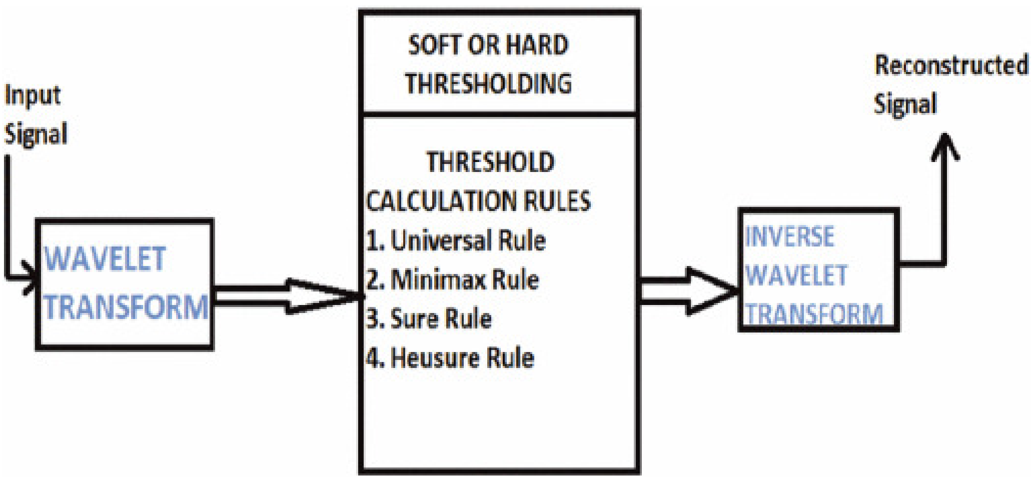

Figure 2: Block diagram of Wavelet based models

The denoising process can be summarized in the following algorithm:

Step 1: Apply Discrete Wavelet Transform (DWT):

Discrete Wavelet Transform is a mathematical technique used to decompose a signal into different frequency components at various scales. In the context of ECG denoising, the noisy ECG signal is subjected to DWT. This involves breaking down the original ECG signal into a set of wavelet coefficients at different levels, also known as 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 2: Choose a Thresholding Method and Determine the Threshold Value (T):

Selecting an appropriate thresholding method is a crucial decision in the denoising process. In this algorithm, several common methods are mentioned: universal, minimax, Rigrsure, and Heursure. The choice of method often depends on the specific characteristics of the noise and the ECG signal. Different thresholding methods have different mathematical foundations and may perform better in certain situations. The selected method should be based on prior knowledge or experimentation.

Once the thresholding method is chosen, the next step is to determine the threshold value (T). This value is critical because it defines the magnitude above which wavelet coefficients will be retained and below which they will be set to zero. The threshold value can significantly impact the quality of the denoised signal.

Step 3: 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's how each type of thresholding works:

Soft Thresholding: In soft thresholding, wavelet coefficients whose magnitudes exceed the threshold value ($|x| > \mathrm{T}$) 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 completely eliminating them.

Hard Thresholding: Hard thresholding retains coefficients whose magnitudes are greater than the threshold value ($|x| > \mathrm{T}$) 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 4: 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 5: Evaluate Performance in Terms of Signal-to-Noise Ratio (SNR):

To assess the effectiveness of the denoising method, it's crucial to quantitatively evaluate its performance. One common 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 it means that the signal is more dominant compared to 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, as well as the evaluation of the denoising performance using SNR, are critical components of this process, ensuring that important cardiac information is preserved while noise is effectively reduced.

Method 6

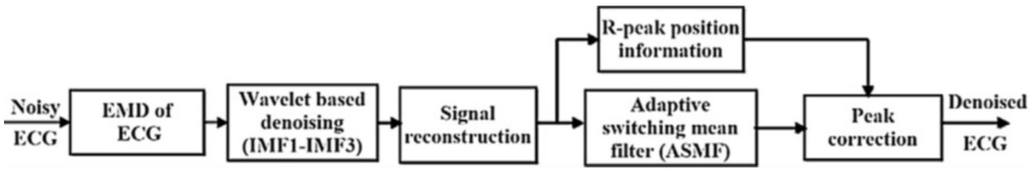

Figure 3: Hybrid Model

The EMD algorithm and wavelet-based algorithm with signal reconstruction algorithm are discussed above.

- 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.

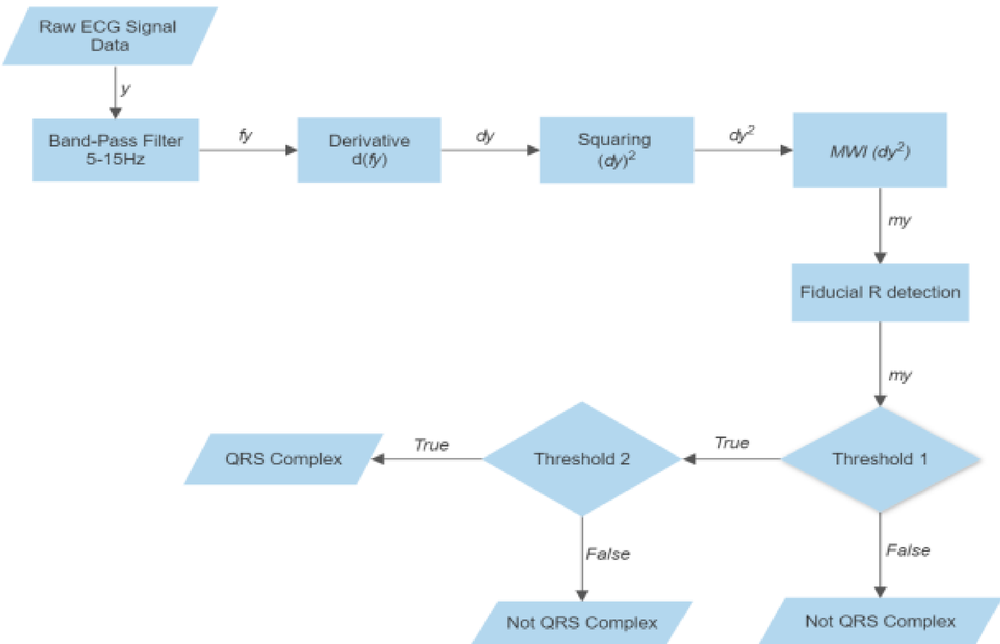

Figure 4: Pan-Tompkin's algorithm

- Adaptive switching mean filter (ASMF) Algorithm[6]:
  1) A particular length of window is taken, and at each iteration, the centre of the window is placed on a test ECG sample.
  2) A threshold value is estimated by calculating the standard deviation of the windowed region.
  3) If the difference between test ECG sample and the mean value of the windowed area is beyond the threshold limit, then it is considered as a corrupted sample, and its value is updated according to the mean value.

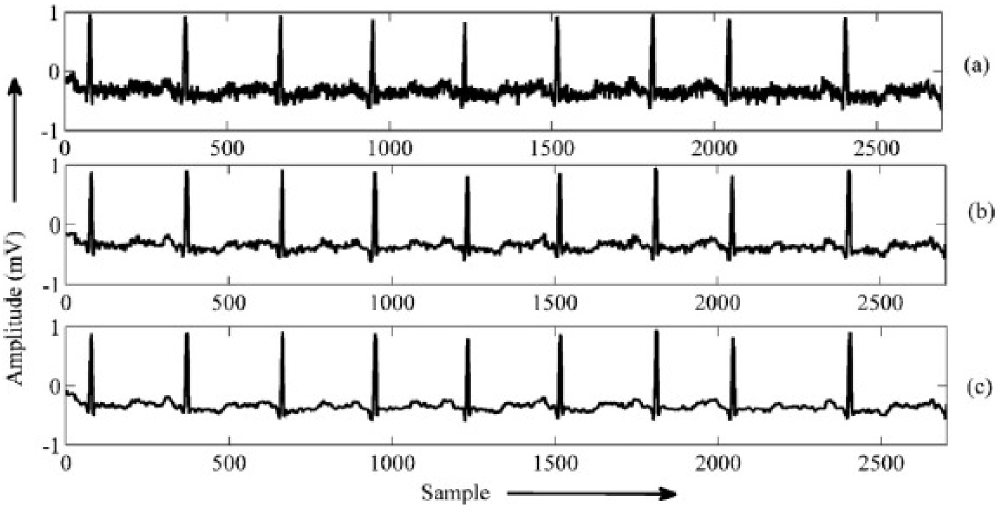

Figure 5: Expected Output (a.Noisy signal b.After EMD denoising c.After using ASMR filter)

4 Progress So Far and the Results

Method 1

We initially focused on understanding the method and its algorithms by doing literature survey. Now we have started with the coding part and made a rough code of how the process will look like. The toolbox and the dataset have been downloaded. The dataset 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 have not yet obtained the results. We will be working on getting outputs for the next phase of our project.

Method 3

1. Took WFDB Toolbox to perform preprocessing steps on MITBIH dataset from Physionet

2. Loaded one of the signal from MITBIH dataset. The baseline wander noise was suppressed using moving average filter. (There are 48 sound in MITBIH dataset.)

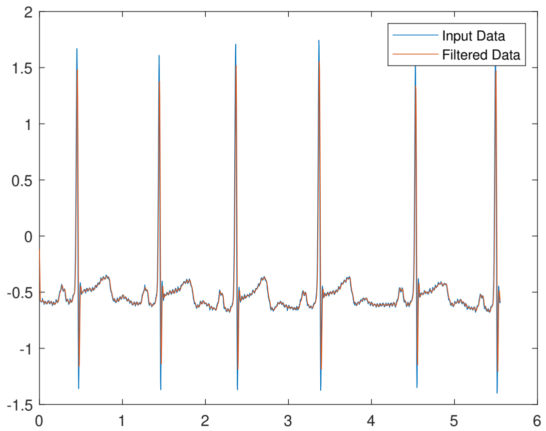

Figure 6: Signal before and after removing baseline wander noise

3. To analyse better DWT, three noises, namely Power line interference , muscle artifact and pink noise was added and plotted with filtered signal from above

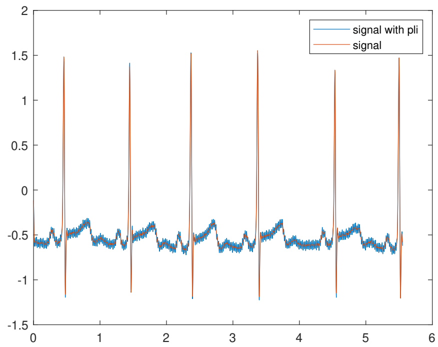

Figure 7: Signal added with Power line interference

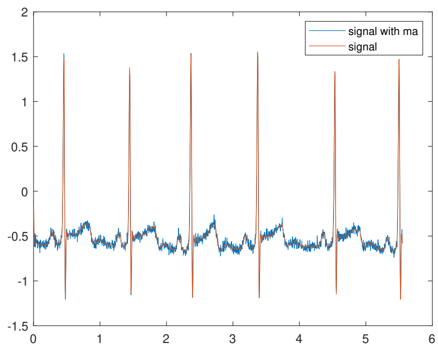

Figure 8: Signal added with Muscle artifact

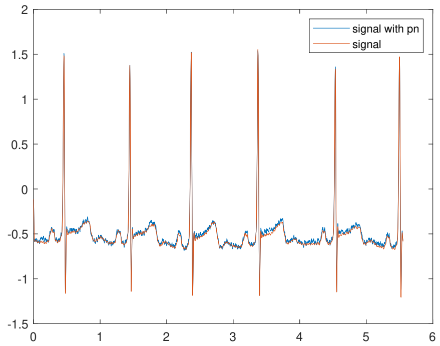

Figure 9: Signal added with pink noise

Method 6

Our hybrid model involves applying additional denoising techniques on already denoised signal. As of now we have developed a part of the ASMF code and the overall structure of the hybrid model. However, output is not ready since it depends on the ECG signal obtained after the first two processes (EMD and wavelet based) which is yet to be developed. But we have verified the code for the ECG data from Experiment 1 provided in DSP lab. This is the result obtained:

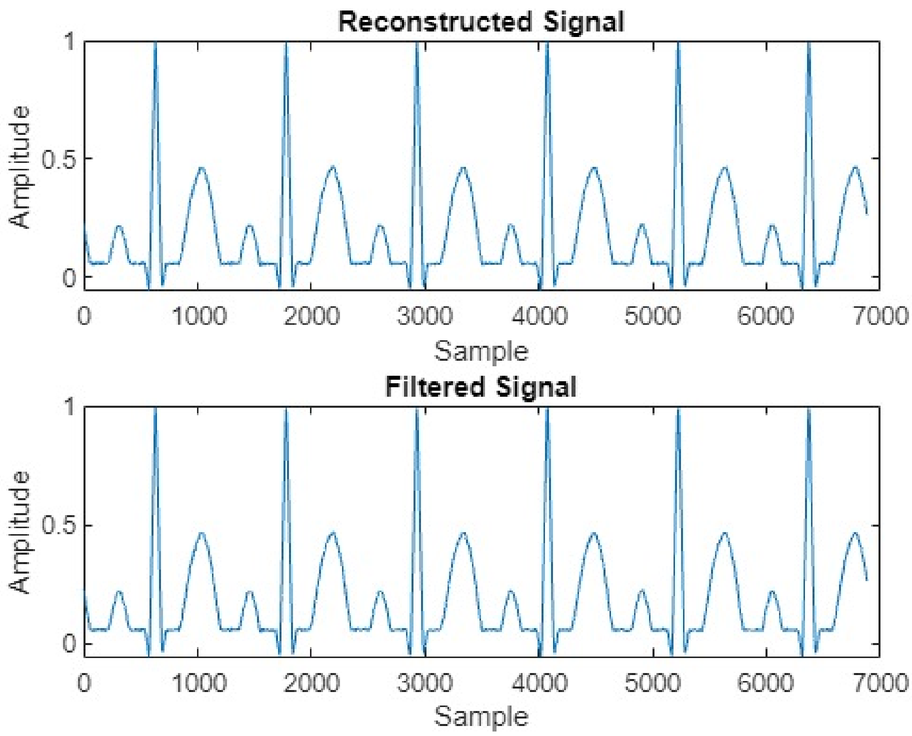

Figure 10: ASMF output

5 Next Steps

Method 1 As mentioned earlier, we have prepared the rough code and we will now focus on getting the outputs. We will be doing the following steps:

- Identify and filter noise-dominant IMFs.
- Apply filtering to noise-dominant IMFs.
- Evaluating the denoising performance.
- Validation, optimization, and documentation.

Method 3

- Transform the noisy ECG signal to wavelet domain for finding DWT coefficients of each level (sub band). While performing DWT, type of wavelet(daubechies, symlet and biorthogonal wavelet family) and level of decomposition will be selected.
- Threshold value will be selected using four thresholding rules and by soft and hard thresholding process, the significant wavelet coefficients from each level are selected.
- Reconstruct the denoised ECG signal from the estimated wavelet coefficients by inverse DWT.
- Different thresholding algorithms will be analyzed and their performances will be evaluated in terms of SNR.

Method 6

- We are yet to develop the Pan-Tompkin's algorithm that involves several steps such as squaring, bandpass filtering, differentiation, integration etc.
- Then once the signal is processed through EMD and wavelet-based techniques, we will apply the R-peak detection algorithm followed by ASMF and then add the R-peak back and combine all the techniques together.
- We will also plot SNR improvement, mean square error and percentage root mean square difference to measure the efficacy of the proposed hybrid model.

6 Summary of the Mid Term Work

At this point in our project, we have successfully completed the literature review, thoroughly comprehending the methodologies associated with the three methods we mentioned earlier. We have started with the practical implementation as code using MATLAB. During this initial stage of coding, we've made significant progress in the task of data preprocessing.

7 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.

[2] Chitrangi Sawant; Harishchandra T. Patii. Wavelet based ecg signal de-noising. *IEEE*.

[3] Harshal Chaudhari; S. L. Nalbalwar; Rashmee Sheth. A review on intrensic mode function of emd. *IEEE*.

[4] Zazia Saidi Abdel-O. Boudraa, Jean-Christophe Cexus. Emd-based signal noise reduction. 2005.

[5] S. Hayakawa M. A. Z. Fariha, R. Ikeura and S. Tsutsumi. Analysis of pan-tompkins algorithm performance with noisy ecg signals. *Journal of Physics: Conference Series*, 2020.

[6] Sushmita Das Manas Rakshit. An efficient ecg denoising methodology using empirical mode decomposition and adaptive switching mean filter. *Biomedical Signal Processing and Control*, 2018.