Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, May : 2023

ECG DENOISING USING ADAPTIVE KALMAN FILTER BANK

Mrs. B. Manjula[1], J. Mounika Sai[2], G. Vineela[3], B. Bhuvana Sri[4], G V S Charani[5]
UG students[2,3,4,5], Department of Electronics and Communication Engineering, Vignan's Institute of Engineering for Women
Mrs. B. Manjula[1], Associate Professor, Department of Electronics and Communication Engineering, Vignan's Institute of Engineering for Women

ABSTRACT:
The field of ECG processing demonstrated the efficiency of model-based Bayesian frameworks. In this paper we propose a novel Bayesian framework that employs a Kalman filter Bank and Expectation maximization(EM) algorithm for ECG processing. This method requires fewer preprocessing steps compared to previous Bayesian techniques and it only needs an R-peak detection step in ECG processing. Using the location of R-peaks, we can separate each ECG beat into two sections: QRS Complex (High-frequency section) and P&T waves (Low-frequency section). The Kalman filter bank in this method is comprised of two independent Kalman filters that denoise the aforementioned high and low- frequency signals. The parameters of these filters are estimated and iteratively updated using the expectation maximization(EM) algorithm. The proposed method was evaluated on various ECG databases that contained signals with morphological alterations and abnormalities such as atrial premature complex(APC), and premature ventricular contractions(PVC). The proposed method was compared with several ECG denoising methods such as wavelet transform(WT), Empirical mode decomposition(EMD), and Band-pass filter(BPF). The results showed that the proposed algorithm had given better performance over benchmark methods from each SNR improvement and Multi-Scale Entropy primarily based weighted distortion(MSEWPRD) viewpoints at low enter SNRs.

Keywords:
ECG denoising, Kalman filter, Bayesian filtering, Expectation Maximization(EM) algorithm

INTRODUCTION:

Before initializing a model-based Bayesian framework, several pre-processing steps need to be taken to ensure accurate results. These steps include detecting R-peaks and extracting EDM (ECG Dynamical model) using an offline optimization technique.

Additionally, polar phase association is necessary to link ECG beats together. Finally, Kalman filter parameters must be calculated and the process noise and measurement noise must be estimated. These steps are to essential ensure the accuracy and effectiveness of the model-based Bayesian framework, and they are required for any similar framework.

In an ECG signal, a single EDM (ECG dynamical model) is assigned, which means that all beats are assumed to have the same respiratory signal. However, in cases where there are significant variations in the shape of the beats, such as during arrhythmia or when the electrodes become disconnected, this assigned EDM is not useful for those beats. However, the MP-EKF method proposed can handle these types of beats using an adaptive fuzzy-based particle when using a Kalman filter for ECG processing, the process and measurement noise matrices are not properly defined beforehand if the noise properties changebetween beats. To cope with this issue, abrand-new Bayesian framework is proposed in this paper, which utilizes a Kalman filter bank and an Expectation maximization(EM) algorithm for ECG processing.

The proposed method requires only R-peak detection before initialization. Each ECG beat is divided into two sections- the QRS complex (high-frequency section) and the P-T waves (low-frequency

section). The QRS segments are concatenated to form high-frequency signals, and the P-T wave is concatenated to form low-frequency signals. These signals are then fed into the proposed Kalman filter bank, which consists of two independent Kalman filters that denoise the high and low-frequency signals.
The parameters of the two Kalman filters are estimated and updated iteratively using the EM algorithm. To handle non-stationary noises, Bryson and Henrikson's technique is utilized for the prediction and update steps inside the Kalman filter bank.

MATHEMATICAL PRELIMINARIES:

KALMAN FILTER:

Kalman filter can also be referred to as linear quadratic estimation (LQE). It is an algorithm that uses a set of measurements with respect and other inaccurate measurements. This filter produces an estimation of unknown variables which can be more accurate than the single measurements observed alone. Kalman filtering contains many technological applications [11]. The variants of the Kalman filter were implemented in various applications such as navigation and control vehicles, denoising signals, navigation, and mainly in spacecraft.

The state-space and measurement model for the discrete-time filter is as follows:

- $\mathbf{x}_k = \mathbf{A}_k \mathbf{x}_{k-1} + \mathbf{w}_{k-1}$ (1(a))
- $\mathbf{y}_k = \mathbf{C}_k \mathbf{x}_k + \mathbf{v}_k$ (1(b))

where $\mathbf{x}_k$, y_k, A_k, and C_k are considered as a state vector, measurement vector, transition matrix, and measurement matrix at time step k. In the same way, v_k and w_k are measurement vectors and process noise vectors at time step k. These noise vectors, uncertainties of measurement, and state dynamics use white Gaussian noise with covariance matrices.
By using equation (1) the discrete Kalman filter algorithm might be summarized in two stages and these stages are shown in the following as the "Prediction Step" and "Update Step".

Prediction step:

- $\boldsymbol{x}_{k|k-1} = \mathbf{A}_k \hat{\boldsymbol{x}}_{k|k-1}$ (2(a))
- $\boldsymbol{P}_{k|k-1} = \mathbf{A}_k \mathbf{P}_{k|k-1} \boldsymbol{A}^T_k + \mathbf{Q}_{k-1}$ (2(b))

Update step:

- $\mathbf{i}_k = \mathbf{y}_k - \mathbf{C}_k \hat{\boldsymbol{x}}_{k|k-1}$ (3(a))
- $\mathbf{S}_k = \mathbf{C}_k \mathbf{P}_{k|k-1} \boldsymbol{C}^T{}_k + R_k$ (3(b))
- $\mathbf{K}_k = \mathbf{P}_{k|k-1} \boldsymbol{C}^T{}_k \mathbf{S}_{k-1}$ (3(c))
- $\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \mathbf{K}_k \mathbf{i}_k$ (3(d))
- $\mathbf{P}_{k|k} = \mathbf{P}_{k|k-1} - \mathbf{K}_k \mathbf{S}_k \boldsymbol{K}^T{}_k$ (3(e))

Where $\hat{\boldsymbol{x}}_{k|k-1}$ and $\hat{\boldsymbol{x}}_{k|k}$ are considered as predicted means and update or estimate the mean of state vector for time step k. In this order, $P_{k|k-1}$ and $P_{k|k}$ is predicted covariance matrix and update covariance matrix for the state vector at time step k. i_k, K_k, and S_k are innovation vectors, Kalman filter gain, and measurement prediction error covariance matrix. Kalman filter can be initiated with initial distribution for state vector. Some parameters like m_o and P_o are chosen based on the system which is under study. The marginal distribution of the Kalman filter can be expressed as the following:

- $P(Y_N) = \Pi^{N}{}_{K=0} p(y_k / y_{k-1}, \ldots\ldots\ldots y_0)$ (4)

  where $Y_N = \{y_1, y_2, \ldots, y_k, \ldots, y_N\}$.

Using the equation (3) prediction step, the log marginal likelihood for the Kalman filter be calculated as:

- $l_k = l_{k-1} - 0.5(i_k{}^T S_{k-1} i_k + \log |S_k| + N_y \log 2\pi)$ (5)

where N_y is the measurement vector Y_k.

The results of the Kalman filter can further be smoothed using methods like backward-pass such as Rauch-Tung-Striebel smoother (RTS). This method can be explained in the following:

- $l_k = P_{k|k} A^T{}_{K+1} P_k{}^{-}{}_{+}{}^{1}{}_{1|k}$ (6(a))
- $\hat{x}_{k|N} = \hat{x}_{k|k} + L_k(\hat{x}_{k+1|N} - \hat{x}_{k+1|k})P$ (6(b))
- $P_{k|N} = P_{k|k} + L_k(P_{k+1|n} - P_{k+1|k})L$ (6(c))

where $\hat{x}_{k|N}$ and $P_{k|N}$ are state estimate smoothed and covariance matrices that can be generated at time step k in the backward pass.

EXPECTATION MAXIMIZATION (EM) ALGORITHM:

The Kalman filter has one problem. To estimate the unknown variables for equations (2) and (3), they should be identified and hence, the EM algorithm can exhibit the outputs for Kalman smoother. The EM algorithm which is also referred to as Expectation Maximization is generally used to identify unknown variables by estimating and updating the variables. This process can be done in two steps.

For a set of parabolic measurements like $Y_N=\{y_1, y_2,\ldots,y_k,\ldots,y_N\}$, the maximum likelihood for parameter set θ and the expression is as shown:

- $\hat{\theta}_{ML}$=arg max $\theta(\log P_\Theta(Y_{1:N}))$ (7)

For unknown linear Gaussian state-space, for the probabilistic parameter set, we desire to attain $\theta=(A_k, C_k, Q_k, R_k, m_o, p_o)$. Using the EM algorithm method and logging the marginal likelihood of the Kalman filter, the ML estimate of θ is obtained in the following two steps:

E-step:

This step can also be referred to as the Expectation step. In this step with the help of the data observed, we can estimate the unobserved data. This involves the expectation of log-likelihood by the estimated parameters of Θ for i^{th} iteration. The equation is expressed as follows:

- $\mathbf{E}[\mathbf{x}_k|\mathbf{y}_{1\text{-}N}] = \hat{\boldsymbol{x}}_{k|N}$ (8(a))
- $\mathbf{S}_{1,1,k} = E[\mathbf{x}_k \boldsymbol{X}^T{}_k|y_{1:N}] = \mathbf{P}_{k|N} + \hat{\boldsymbol{x}}_{k|N}\hat{\boldsymbol{x}}^T{}_{k|N}$ (8(b))
- $\mathbf{S}_{1,0,K} = E[\mathbf{x}_k \boldsymbol{X}^T{}_{k-1}|\mathbf{Y}_{1:N}] = \mathbf{P}_{k,k-1|N} + \hat{\boldsymbol{x}}_{k|N}\boldsymbol{x}^T{}_{k-1|N}$ (8(c))
- $\mathbf{S}_{0,0,k} = E[\mathbf{x}_{k-1} \boldsymbol{X}^T{}_{k-1}|\mathbf{Y}_{1:N}] = \mathbf{P}_{k-1|N} + \hat{\boldsymbol{x}}_{k-1|N}\boldsymbol{X}^T{}_{k-1|N}$ (8(d))
- $\mathbf{P}_{k,k-1|N} = \mathbf{P}_{k|k}\boldsymbol{L}^T{}_{k-1} + \mathbf{L}_k(\mathbf{P}_{k+1,k|N} - \mathbf{P}_{k|k})\boldsymbol{L}^T{}_{k-1}$ (9)

M-step:

This step can also have referred to as the Maximization step. In this step with the help of the data estimated from the E-step or Expectation step, we update the unobserved data that is observed in the above step. This involves the re-estimation and by solving these equations, the updated parameters are shown in the following:

- $\mathbf{A}^{(i)} = (\sum^N{}_{k=2}\mathbf{S}_{1,0,k})(\sum^N{}_{k=2}\mathbf{S}_{0,0,k})^{-1}$ (10(a))
- $\mathbf{Q}^{(i)} = \frac{1}{N-1}\left(\sum_{K=2}^{N} S_{1,1,k} - A^{(i)}\left(\sum_{K=2}^{N} S_{1,0,k}\right)^T\right)$ (10(b))
- $\mathbf{C}^{(i)} = (\sum^N{}_{k=1}\mathbf{Y}_k \boldsymbol{X}^T{}_{k|N})(\sum^N{}_{k=1}\mathbf{P}_{k|N})^{-1}$ (10(c))
- $\mathbf{R}^{(i)} = \frac{1}{N}\left(\sum_{K=1}^{N} Y_k \hat{X}_{K|N}^T\right)(Y_K - C^{(i)}\hat{X}_{K|N})^T - C^{(i)}\mathbf{P}_{k|N}(C^{(i)})^T)$ (10(d))
- $\mathbf{P}_0^{(i)} = \mathbf{P}_{1|N}$ (10(e))
- $\boldsymbol{m}_0^{(i)} = \hat{\boldsymbol{x}}1|N$ (10(f))

HANDLING COLOURED MEASUREMENT NOISE:

When the parameters of the Kalman filter are chosen correctly, we can estimate the unknown variables optimally in a white Gaussian environment. But when either the process or measurement noises or both of them are colored, the Kalman filter results might not be optimal. For example, a colored noisy environment is as shown in the following:

- $\mathbf{x}_k = \mathbf{A}_k \mathbf{X}_{k-1} + \mathbf{w}_{k-1}$ (11(a))
- $\mathbf{y}_k = \mathbf{C}_k \mathbf{x}_k + \mathbf{v}_k$ (11(b))
- $\mathbf{v}_k = \boldsymbol{\varphi}_k \mathbf{v}_{k-1} + \mathbf{e}_k$ (11(c))

here φ_k is considered aa s measurement of the noise transition matrix and e_k is the white Gaussian noise along with the covariance matrix R_k. Here $e_k \sim N(0, R_k)$. The values in φ_k describe what type of noise is present in measurements and the small values indicate the measurement noise is nearly similar to the stationary white Gaussian noise. The system in (11) is defined for non-stationary environments where we can implement the Kalman filter using a method known as "Measurement Time Difference". In the process, the pseudo-measurement is defined to convert the colored measurement noise into a white measurement noise and it is shown in the following:

- $\mathbf{z}_k = \mathbf{y}_{k+1} - \boldsymbol{\varphi}_k \mathbf{y}_k$ (12)

With the help of equation (12), the parameters modified in equations (2) & (3) are:

- $\mathbf{C}_{k,new} = \mathbf{C}_k \mathbf{A}_k - \boldsymbol{\varphi}_k \mathbf{C}_k$ (13(a))
- $\mathbf{S}_k = \mathbf{Q}_k \boldsymbol{C}^T{}_K$ (13(b))
- $\mathbf{R}_{k,new} = \mathbf{C}_k \mathbf{Q}_k \boldsymbol{C}^T{}_K + \mathbf{R}_k$ (13(c))
- $\mathbf{J}_k = \mathbf{S}_k \boldsymbol{R}^{-1}_{k,new}$ (13(d))
- $\mathbf{Q}_{k,new} = \mathbf{Q}_k + \mathbf{S}_k \boldsymbol{R}^{-1}_{k,new} \boldsymbol{S}^T{}_K$ (13(e))
- $\mathbf{A}_{k,new} = \mathbf{A}_k - \mathbf{J}_k \mathbf{C}_{k,new}$ (13(f))

here $\mathbf{A}_{k,new}$, $C_{k,new}$, $\mathbf{Q}_{k,new}$, and $\mathbf{R}_{k,new}$ are the building parameters of the Kalman filter of the system in (11). With the help of these equations, the steps Prediction step and Update step which are designed for the Kalman filter system for the equation (11) are:

Prediction step:

- $\boldsymbol{x}_{k|k-1} = \mathbf{A}_{k,new} \hat{\boldsymbol{x}}_{k-1|k-1} + \mathbf{J}_k (\mathbf{z}_{k-1} - \mathbf{C}_{k,new} \hat{\boldsymbol{x}}_{k-1|k-2})$ (14(a))
- $\mathbf{P}_{k|k-1} = \mathbf{A}_{k,new} \mathbf{P}_{k-1|k-1} \boldsymbol{A}^T{}_{k,new} + \mathbf{Q}_{k-1,new}$ (14(b))

Update step:

- $\mathbf{i}_k = \mathbf{z}_k - \mathbf{C}_{k,new} \hat{\boldsymbol{x}}_{k|k-1}$ (15(a))
- $\mathbf{S}_k = \mathbf{C}_{k,new} \mathbf{P}_{k|k-1} \boldsymbol{C}^T{}_{k,new} + R_{k,new}$ (15(b))
- $\mathbf{K}_k = \mathbf{P}_{k|k-1} \boldsymbol{C}^T{}_{k,new} \boldsymbol{S}^{-1}_k$ (15(c))
- $\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \mathbf{k}_k \mathbf{k}_i$ (15(d))
- $\boldsymbol{P}_{k|k} = \mathbf{P}_{k|k-1} - \mathbf{k}_k \mathbf{S}_k \boldsymbol{k}^T{}_k$ (15(e))

PAN- TOMPKINS METHOD:

The Pan- Tompkins algorithm is commonly used to detect QRS complexes in ECG. This algorithm applies a series of filters to highlight the frequency content of this rapid heart depolarization and removes the background noise. Then, it squares the signal to amplify the QRS contribution, which makes identifying the QRS complex more straight forward.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, May : 2023

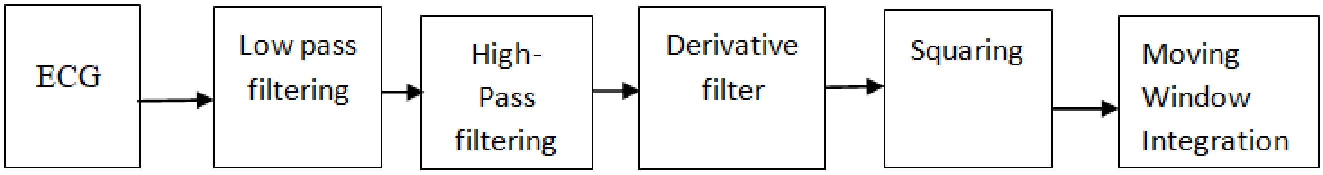

Figure1. Block diagram of the Pan-Tompkins method

LITERATURE SURVEY:

[1] Nasser Mourad proposed "ECG denoising based on successive local filtering" In this paper, a new algorithm for denoising ECG data contaminated by wideband noise is proposed. This kind of noise signal is usually considered an additive white Gaussian noise(AWGN). A successive local filtering approach was developed in this paper to remove wideband noise from recorded ECG data. In this proposed algorithm, a segmentation procedure was developed to segment the recorded ECG data such that each element approximately contains one of the four components. A clean ECG data was modelled as a combination of the four components named QRS-complexity-wave, TP-segment, and P-Wave. In this model, algorithms can be classified into four different classes.

[2] Nadeem Iqbal proposed "Noise Reduction in ECG Signal using an Effective Hybrid Scheme" In this paper, the hybrid denoising algorithm for ECG signal based on FSSTH and NLM consists of the following steps:

The first step is to collect the ECG signal that needs to be denoised.The second step is to decompose the noisy ECG signal using the Fast S-Transform with Hilbert (FSSTH) and obtain an ensemble of band-limited intrinsic mode functions(IMFs) The FSSTH is a modified version of the Fast S-Transform that uses the Hilbert transform to obtain a complex-valued time-frequency distribution.The third step is to estimate thescaling exponent concerning each IMF using Detrended Fluctuation Analysis (DFA) to determine the number of IMFs obtained from the FSSTH.The fourth step is to evaluate each IMF via the DFA and determine the threshold for each IMF based on the Hurst exponent.The fifth step is to eliminate the noisy IMFs based on thresholding criteria. IMFs with a threshold below a certain value.

[3] Hamed DanandehHesar and Maryam Mohebbi proposed "A Multi-Rate Marginalized Particle Extended Kalman Filter for P and T Wave Segmentation in ECG Signals" The paper introduces the use of FSSTH in ECG signal processing, an adaptive equation for determining the number of modes, and the use of scaling exponent from DFA as a threshold for separating signal and noise.The marginalized particle prolonged Kalman filter (MP-EKF) is a mathematical version that may be used to do away with noise from electrocardiogram (ECG) signals. It is effective in dealing with nonlinearities in the ECG signals. This model has also been used to identify specific features in the ECG signal, such as the P and T waves. A new approach has been proposed that uses a multi-rate version of the MP-EKF to estimate the P and T waves more accurately. This new approach adjusts the behavior of the particles used in the model to better match the ECG signal trajectory. After the ECG signal has been filtered, a new algorithm based on morphological operations is used to identify the fiducial points of the P and T waves. This algorithm combines several well-known operations to produce more accurate results. The proposed algorithm was tested on a database of ECG signals and compared to other Bayesian frameworks. The results showed that the new approach outperformed other methods in accurately identifying the P and T waves in the ECG signal.

[4] Hamed Danandeh and Maryam Mohebbi proposed "An Adaptive Particle Weighting strategy for ECG Denoising Using Marginalized Particle Extended Kalman Filter". This paper focuses on a model-based Bayesian denoising framework that uses a marginalized particle-extended Kalman filter (MP-

EKF Variational Mode Decomposition (VMD), and a fuzzy-based adaptive particle weighting strategy to improve denoising performance. The framework is designed to work well even when the morphology of the signal does not comply with the pre-defined dynamic model. The proposed strategy adapts the behavior of MP-EKF to the acquired measurements in different input signal-to-noise ratios (SNRs).At low input SNRs, the proposed strategy reduces the particle's trust level in the measurements and increases their trust level to a synthetic electrocardiogram (ECG) constructed using the feature parameters of the ECG dynamic model (EDM). At high input SNRs, the particle's trust level in the measurements is increased while the trust level in the synthetic ECG is decreased.

PROPOSED METHOD:

In this section, we design an adaptive Kalman filter bank for ECG denoising. The electrocardiogram (ECG or EKG) signal is a time-varying electrical signal that provides the electrical activity of the heart. The ECG signal provides important diagnostic information about the heart's health and rhythm. During the recording of ECG signals, they may have corrupted with various types of unwanted interference such as muscle artifacts, electrode artifacts, power line noise, and respiration interference, and are distorted in such a way that it can be difficult to perform medical diagnosis, physiological therapy, or arrhythmia monitoring. Consequently, signal processing on ECGs is required to remove noise and interference signals for successful clinical applications.

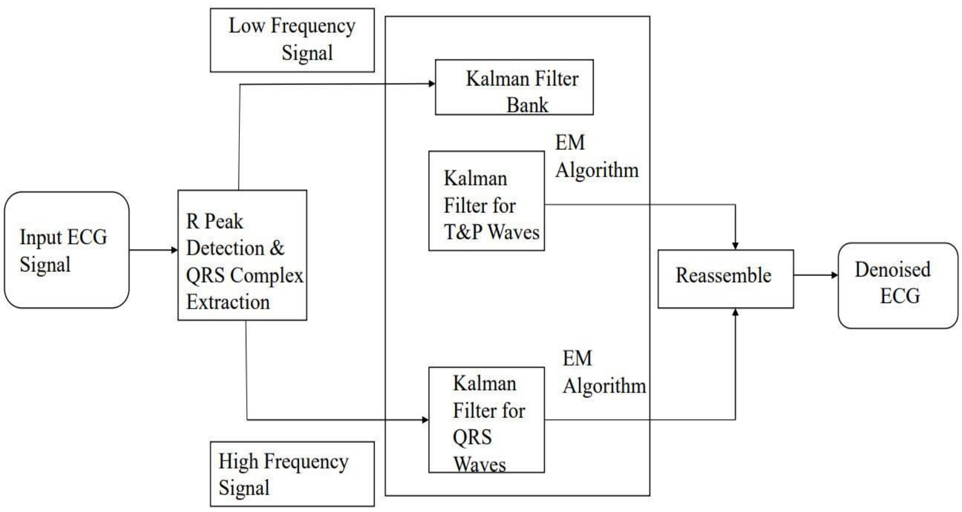

Figure2. Flow chart of the proposed method

This paper proposes a novel Bayesian framework that employs a Kalman filter bank and EM algorithm for ECG processing. This method requires much fewer pre-processing steps compared to other Bayesian techniques. The R peak detection is the only pre-processing step needed for our algorithm and R-peaks of input ECG signal can be extracted using Pan- the Tompkins method. One of the most commonly used methods is the QRS detection algorithm introduced by Pan and Tompkins. This algorithm is the most widely used and most frequently cited approach for the extraction of QRS complexes from an ECG signal. This algorithm utilizes the amplitude, slope, and width of an integrated window to identify the R-peaks in the QRS complex. The algorithm consists of a band-pass filter (Low Pass and High Pass Filters), derivatives, a squaring function, a moving window integration(WMI), a threshold, and a decision as shown in figure (). To adapt to the changes in QRS morphology and heart rate, the threshold was automatically adjusted with the parameter in the decision stages. By using the R-peak of an ECG signal, we can separate each ECG beat into two parts: QRS complex and P-T waves.

In this paper, we employed an Adaptive Kalman filter bank(AKFB) is a signal processing technique used for denoising ECG signals it consists of two independent Kalman filters, one Kalman filter is designed to denoise QRS complexes and the other Kalman filter is designed to denoise P-T waves. An independent EM algorithm is used for each Kalman filter. Using the iterative process of the EM algorithm and RTS smoother equations, the filter bank denoises the aforementioned signals. Finally, the two denoised signals are reassembled to construct the denoised ECG signal. The AKFB adaptively adjusts its parameters based on the noise level in the ECG signal, resulting in better denoising performance compared to other methods. Unlike convolution-based filters, the size of the input is equal to the size of the output in the Kalman filter framework. Therefore, mismatching problems in the reassembling process is ignored in this algorithm. For managing the nonstationary noises more effectively, we propose to use modified model-defined equations instead of the standard model-defined equation. This algorithm contains one or more post-processing stepsto suppress baseline drifts in non-stationary noises. Therefore, we use a median filter to remove baseline drifts. Moreover, our algorithm can be used in situations such as ventricular tachyarrhythmia(VT) or sudden cardiac death(SCD), premature ventricular complex(PVC), etc., in which ECG signals lose most of the features and characteristics and exhibit different dynamics.

EXPERIMENTAL RESULTS:

The performance of the proposed algorithm was investigated on a specific type of medical data called ECG segments. The ECG segments were taken from the physio bank. The examples of several ECG signals are atrial premature complex (APC), and premature ventricular contraction(PVC) which are related to the MIT-BIH arrhythmia(ADB) database as shown in figure (3). Here we are taking the atrial premature complex(APC) signal. The duration of each segment from this database was 1-2 minutes.
The denoising performance of the proposed method was investigated on noise like Artificial white Gaussian noise and real muscle artifact noise which are extracted from the MIT-BIH noise stress test database. The noised APC ECG signal is shown in figure (4).

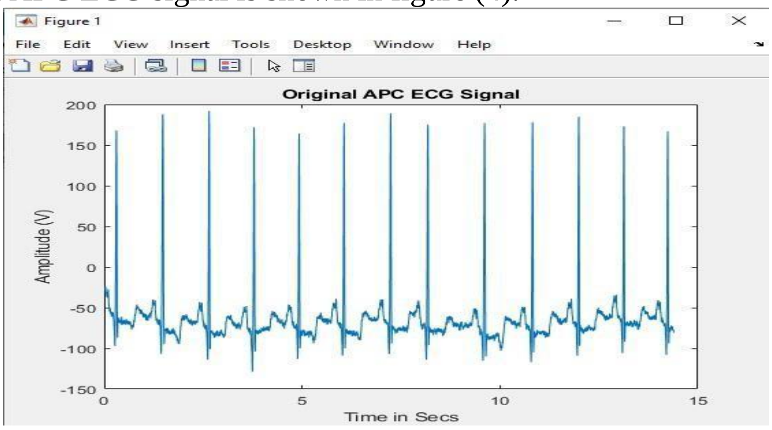

Figure3. APC ECG Signal

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, May : 2023

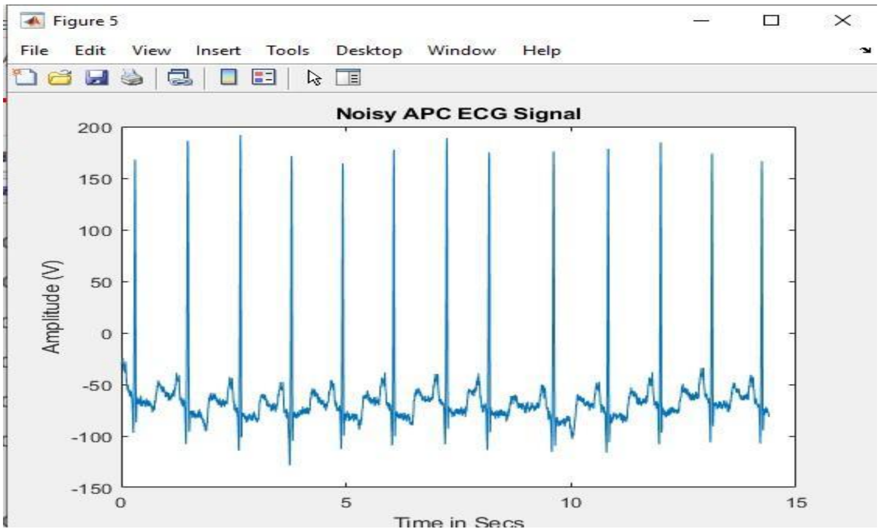

Figure 4. Noisy APC ECG Signal

Initially, this method needs an R-peak detection step in ECG processing. The R-peak of the ECG signal can be extracted using the Pan-Tompkins method. The Pan-Tompkins method consists of a Low Pass filter (LPF), High pass filter(HPF), Differentiator, squaring method, and a moving window integrator as shown in the block diagram figure (1). The output of each step of the Pan-Tompkins method is shown in the figures (5 -10). Using the R-peak detection, we can separate each ECG beat into two sections: QRS Complex (High-frequency section) and P-T waves (Low-frequency section) as shown in figure (11) and figure(12) respectively.

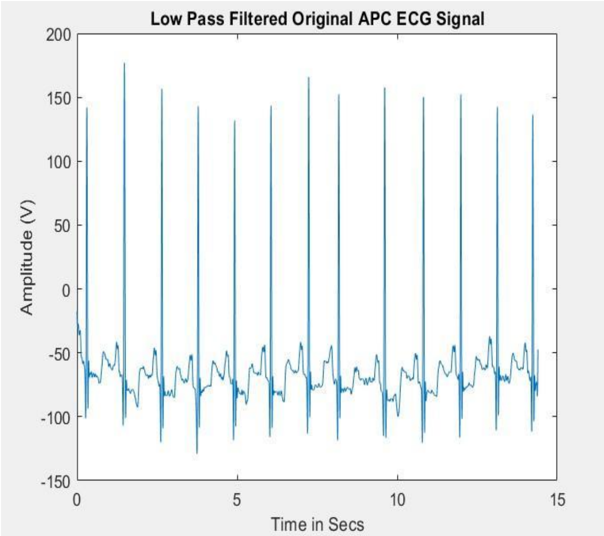

Figure 5. Low pass filtered ECG signal

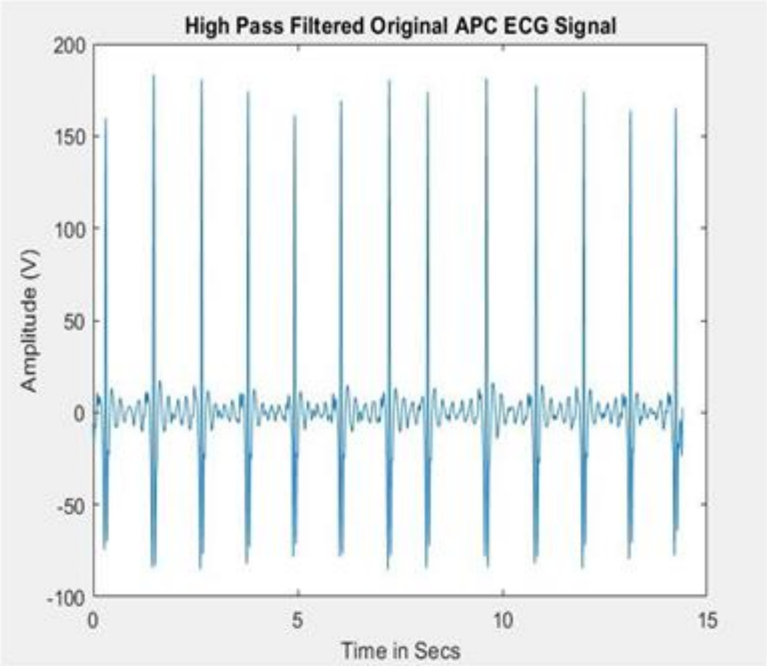

Figure 6. High-pass filtered ECG signal

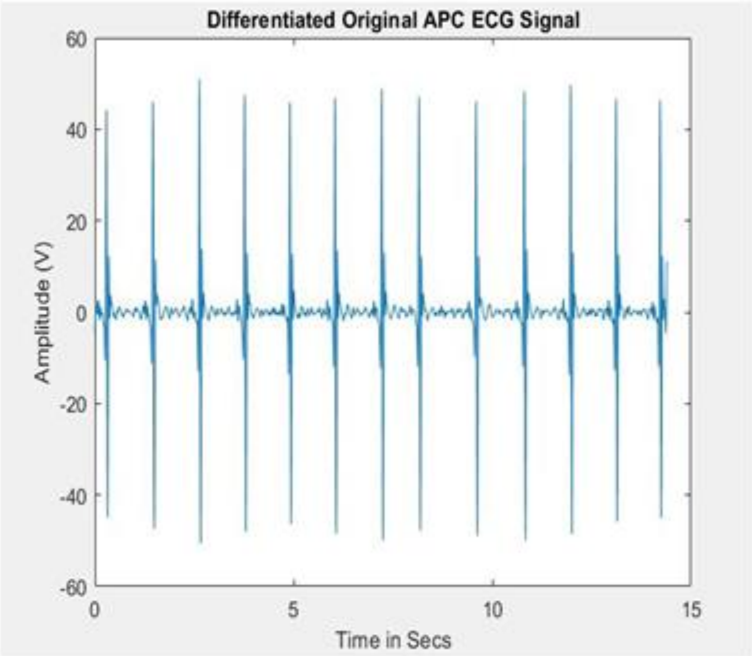

Figure7. Differentiated ECG signal

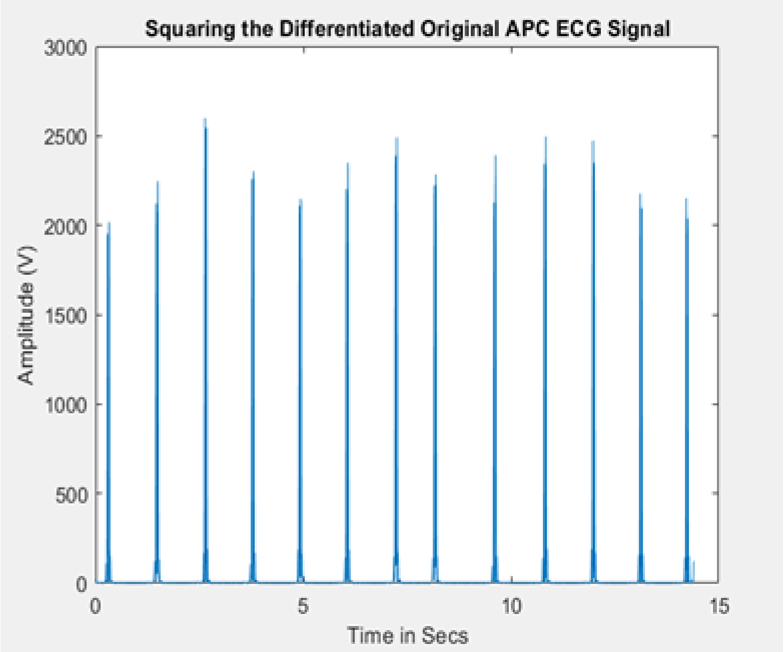

Figure 8.Squaring the differentiated signal

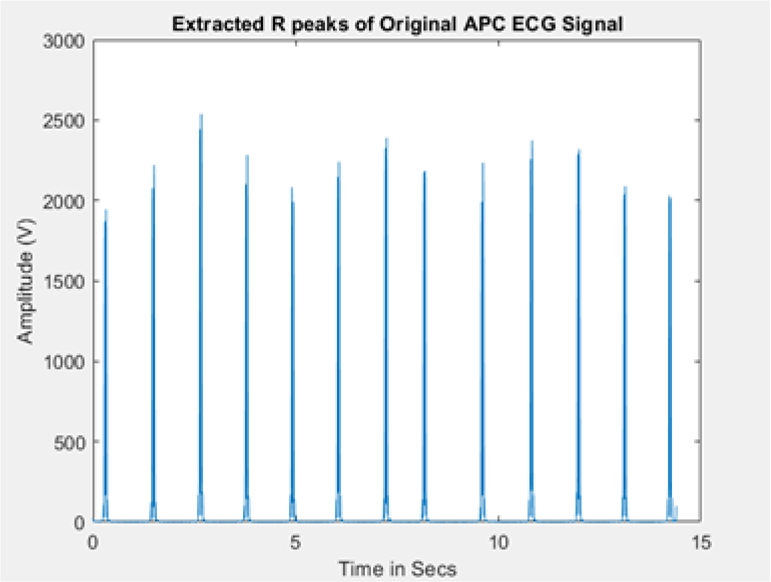

Figure 9. Extracted R peaks of ECG signal

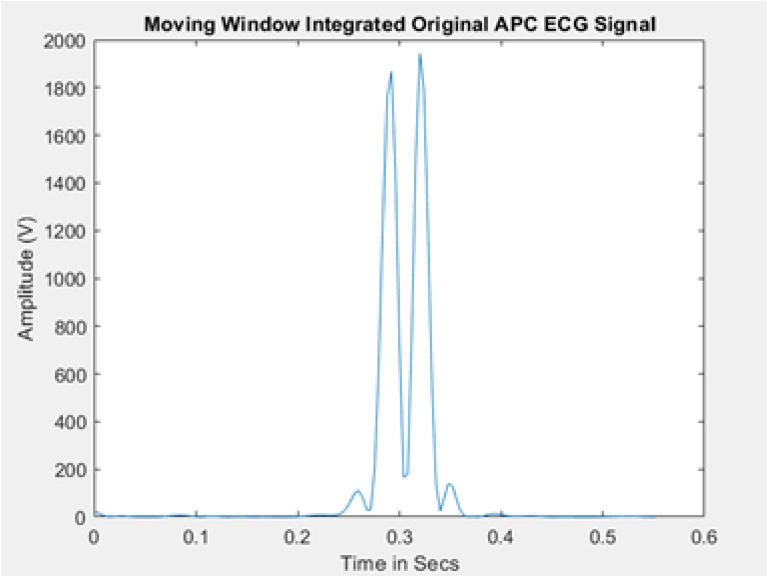

Figure 10. Moving window Integrator of ECG

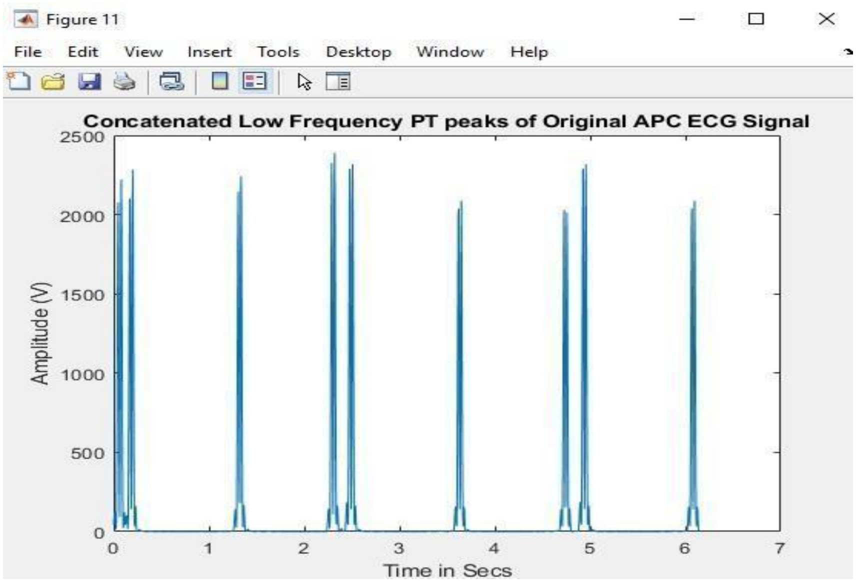

Figure 11. Concatenated Low-Frequency PT peaks of Original APC ECG Signal

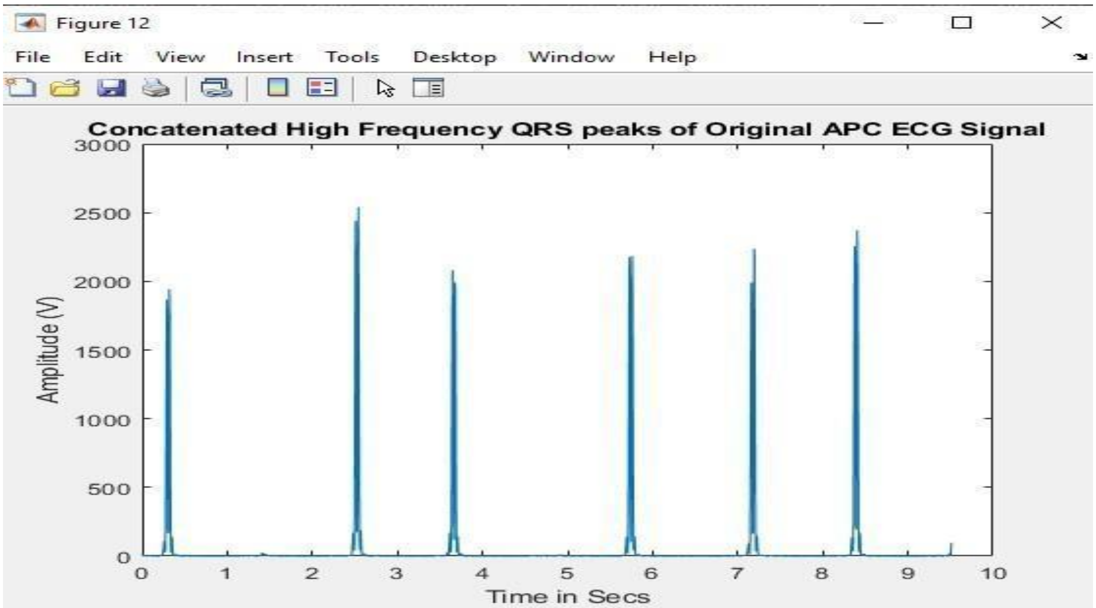

Figure 12. Concatenated High-Frequency QRS Peaks of Original APC ECG Signal

An adaptive Kalman filter bank was proposed in this paper as a technique used to denoise ECG signals. The Kalman filter bank consists of two independent Kalman filters used for denoising the aforementioned ECG segments. The parameters of each Kalman filter are estimated and adaptively approximated using EM(Expectation-Maximization) algorithm. There are a few differences in the morphologies of APC beats and normal beats. Our algorithm managed to suppress the noise and adapt its parameters to keep track of both normal and abnormal beats. Our algorithm preserved the diagnostic features of ECG signals for low SNR. The denoising performance of the adaptive Kalman filter bank in the presence of a noisy ECG signal is shown in fig.(13).

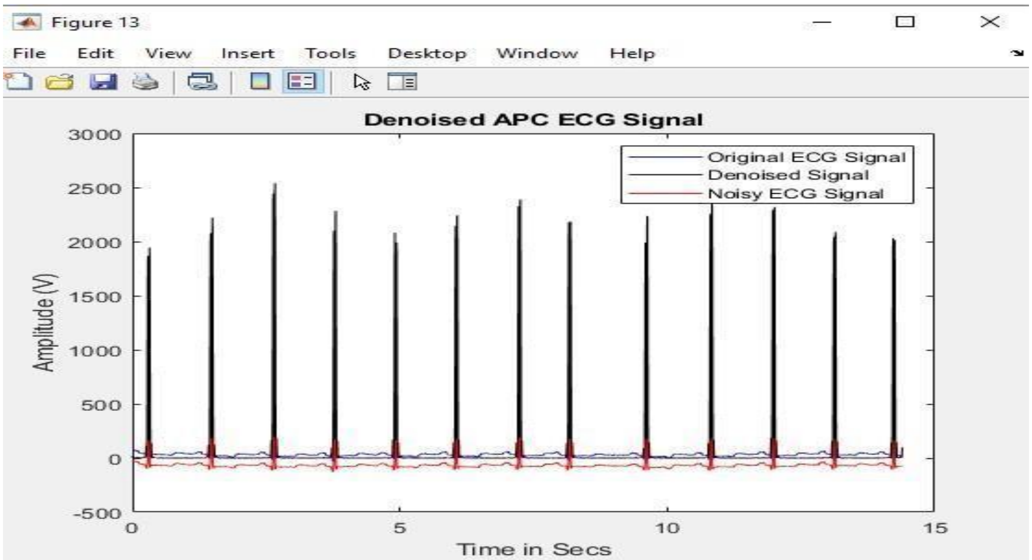

Figure13. Denoised APC ECG Signal

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, May : 2023

We calculated the SNR improvement metric for low SNRs -6, -4,-2,0,2,4,6,8,10 for the APC database as shown in the figure. (14). As input SNR decreases from 10 dB to -6 dB, the performance of our denoising framework exhibits the best results from the SNR improvement viewpoint.

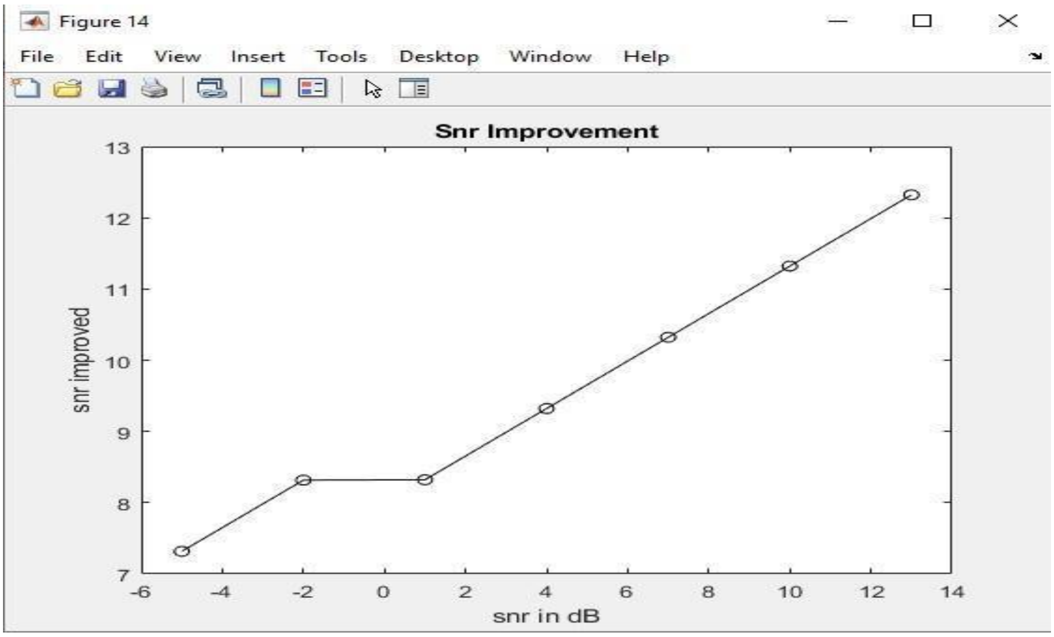

Figure14. SNR improvement

The improvement in the MSEWPRD metric is considered for qualitative assessment. MSEWPRD stands for Multi-scale Entropy-based weighted distortion measure is used for compressed Electrocardiogram (ECG) signals. This measure is a weighted percentage root mean square difference(WPRD) between the sub-band coefficients of the original and compressed signals with weights equal to the multiscale entropies of the corresponding sub-bands. This qualitative measure represents how well a denoising algorithm preserves the diagnostic features of the original ECG signal. We calculated the multi-scale entropy-based weighted distortion (MSEWPRD) metric for low SNRs from 10 dB to -6 dB for the APC database as shown in fig.(15).

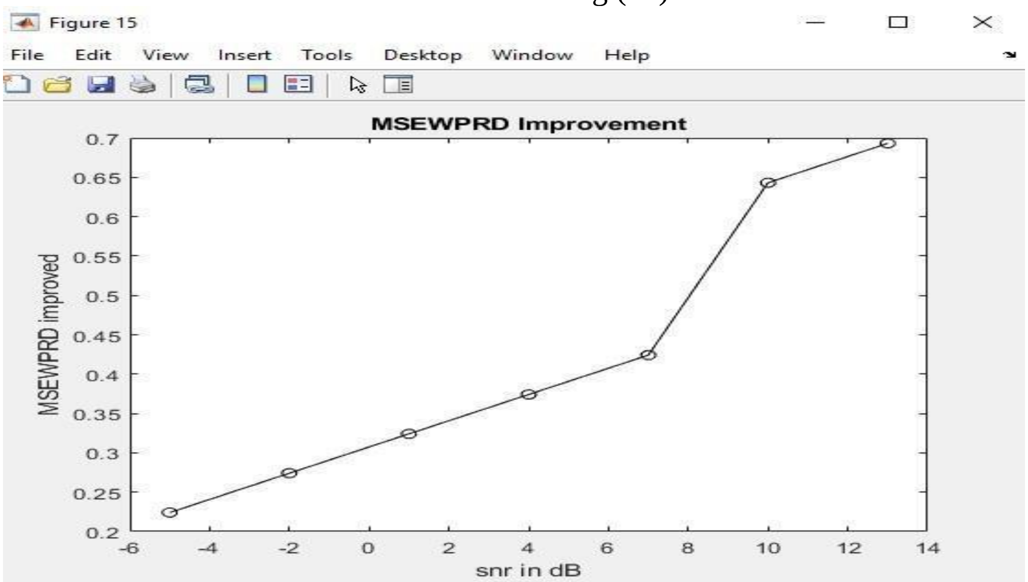

Figure15. MSEWPRD Improvement

This Adaptive Kalman filter bank exhibited good performance at low input SNRs in both SNR stationary and non-stationary environments from both SNR improvement and MSEWPRD viewpoints. This filter does not need a predefined model and can adapt itself to different ECG dynamics and morphologies in stationary /nonstationary environments.

CONCLUSION:

In this paper, the adaptive Kalman filter bank is presented that overcomes the limitation of model-based filtering by handling signals with different morphologies without using a predefined model. It compares different techniques used to remove unwanted noise from electrocardiogram (ECG) signals. ECG signals are used to monitor the electrical activity of the heart and are often used to diagnose heart conditions. However, ECG signals can be contaminated by unwanted noise from various sources. This is particularly useful in applications such as Halter monitoring, where ECG signals contain various types of beats and dynamics. Additionally, the proposed filter bank uses simple and fast pre-processing steps instead of time-consuming heavy pre-processing steps. It has shown good performance at low-input SNRs in both stationary and non-stationary environments from both SNR improvement and MSEWPRD perspectives. The paper also compares the proposed method with popular ECG denoising techniques such as wavelet transform, empirical mode bandpass, and a bandpass filter and demonstrates that the proposed method outperforms these methods in the presence of various ECG morphologies at low input SNRs in both stationary and non-stationary environments. To remove baseline wander we suggest using an empirical mode decomposition-based approach. The paper aimed to provide a better understanding of which techniques are most effective in removing unwanted noise from ECG signals.

REFERENCES:

1. Hamed DanandehHesar and Maryam Mohebbi**, "An Adaptive Kalman Filter Bank for ECG Denoising",** *IEEE Journal of Biomedical and Health Informatics*, 21, 3, 635-644, 2020.
2. H. Hesar, and M. Mohebbi, "ECG Denoising Using Marginalized Particle Extended Kalman Filter with an Automatic Particle Weighting Strategy," *IEEE Journal of Biomedical and Health Informatics*, 21, 3, 635-644, 2016.
3. H. D. Hesar and M. Mohebbi "An Adaptive Particle Weighting Strategy for ECG Denoising Using Marginalized Particle Extended Kalman Filter: An Evaluation in Arrhythmia Contexts," *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 6, pp. 1581-1592, 2018.
4. B. R. Manju, and M. R. Sneha, "ECG Denoising Using Wiener Filter and Kalman Filter," *Procedia Computer Science* 171, 273–281, 2020.
5. P. Bing, W. Liu, Z.Y. Wang, Z. Zhang, "Noise reduction in ECG signal using an effective hybrid scheme," *IEEE Access*, vol. 8, pp. 160790-160801, 2020.
6. N. Mourad, "ECG denoising based on successive local filtering," *Biomedical Signal Processing and Control*, vol. 73, 103431, 2022.
7. The MIT-BIH Normal Sinus Rhythm Database. PhysioNet, Cambridge, MA [Online]. Available: http://www.physionet.org/physiobank/database/nsrdb/
8. The MIT-BIH Noise Stress Test Database. PhysioNet, Cambridge, MA [Online]. Available: https://www.physionet.org/physiobank/database/nstdb/
9. The MIT-BIH Arrhythmia Database [Online].Available:http://physionet.org/physiobank/database/mitdb/
10. Nalajala P, Supraja CD, Deepthika NR, Godavarthi B, Rani KP. Analysis and Optimization of FIR Filters Using Parallel Processing and Pipelining. InFirst International Conference on Artificial Intelligence and Cognitive Computing: AICC 2018 2019 (pp. 667-678). Springer Singapore.

11. Nalajala P, Naik MC, Gopatoti A, Godavarthi B. SPEECH ENHANCEMENT USING COMBINATION OF DIGITAL AUDIO EFFECTS AND KALMAN FILTER. Journal of Fundamental and Applied Sciences. 2018 May 18;10(6S):2839-49.