Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 9
September 2023

Denoising of Power line interference at Negative SNR Contaminated Electrocardiogram signal using Kalman Filter

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Abstract-Identifying and determining various human illnesses requires a phase of visual inspection of biological signals by medical professionals. An effective and non-invasive marker for arrhythmia prevention and identification is the electrocardiogram (ECG). ECG signals are prone to noise contamination in real-world environments, which could result in incorrect interpretation. Thus, the denoising of the ECG has received much attention to providing precise diagnosis and monitoring. Therefore, this paper offers ECG denoising in highly contaminated environments using a Kalman filter (KF). The effectiveness of the proposed method has been evaluated by addingpowerline interference (PLI) at both 50 and 60 Hz at -30 to -10 dB input signal-to-noise ratio (SNR) to the Electrocardiograph record from the MIT-BIH arrhythmia databases. The obtained output SNR (for 50 Hz: 20.82-22.13 dB &for 60 Hz: 21.85- 23.74 dB) divulges the superiority of the KF methodology while assessing it with the notch filter (for 50 Hz: 12.04-16.36 dB and for 60 Hz: 10.75-12.78 dB).

Keywords: -Electrocardiogram, power line interference, signal-to-noise ratio, notch filter, Kalman filter

Introduction

In the View of the World Health Organization (WHO), cardiovascular diseases (often referred to as CVDs) are the prominent reason for death across the globe [1]. Recent research from the American Heart Association (AHA) [2] found that cardiovascular diseases were responsible for nearly one fatality in every three that occurred in the United States (US) in 2017. Arrhythmia is the cardiovascular disease that is most strongly linked to the possibility of an unexpected death [3]. A heartbeat that beats at an irregular rate or rhythm is referred to as arrhythmia. This condition arises when the natural rhythm of the patient's heart does not synchronize adequately with the signals of electrical in the heart. The electrocardiogram (ECG) is an indication commonly used for effectively evaluating and judging arrhythmia. It is a low-cost, efficient, and non-invasive indicator. Biomedical signals, such as ECG recordings, are susceptible to disturbance from power line interference (PLI). The patient, the electrical wiring, and the electrocardiograph are all usceptible to electric fields emanating from nearby power lines. Electrode-to-skin impedance mismatches can cause voltage-reading discrepancies, which are subsequently amplified at the device's output. Although PLI can be mitigated using a well-designed recording setup (with wires shielding and amplifiers with excellent common mode rejection), these actions are rarely enough. PLI out shine's the ECG in terms of amplitude, especially with advancements in sensor technology toward less invasive sensors like textile electrodes and capacitive electrodes [1]. The frequency glad of the ECG (the QRS complex's delighted frequency) intersects with the PLI frequency, making it difficult to refine PLI from ECG noted even though PLI filtering is a rather developed domain [2]-[10]. An effective and non-invasive marker for arrhythmia prevention and identification is the electrocardiogram (ECG). ECG signals are prone to noise contamination in real-world environments, which could result in incorrect interpretation. Therefore, the denoising of the ECG has received much attention to providing precise diagnosis and monitoring. This noise must be reduced to enable doctors to make more accurate diagnoses of conditions affecting the heart.

Literature Survey

In earlier work, PLI was eliminated by developing a bandpass filter with a Threshold frequency value of 50Hz using digital filtering methods [1]. Similarly, finite impulse response (FIR) filters are recommended to employ fewer taps to eliminate PLI [2, 3]. The FIR method asserts that it is superior to a conventional FIR filter for attenuating PLI. Another traditional technique for eliminating PLI from noisy ECG is the notch filter [4, 5]. However, creating a high-quality factor is complex, vulnerable to artifacts, and prone to sudden instability. Therefore, adaptive notch filters that can change based on specific frequency as well as noise or signal components are desirable. In the literature, several adaptive notch filters that may modify the factor quality adaptively are proposed. In addition to these methods, approaches based on decomposition [6–9], like discrete wavelet transform (DWT) and packet wavelet, are well known for eliminating 60 Hz PLI. These techniques are ineffective in environments with severe noise contamination, though. Researchers also recommend the discrete wavelet transform (DWT) with adaptive dual thresholding in addition to these strategies [10]. With and without references, gradient-based adaptive filters are utilized to remove PLI from the ECG signal[11–13]. Some samples must continue to follow the initial ECG shape after starting transient for these adaptive filters. The electrical standard states that the change in PLI frequency is insignificant, so the variance in PLI when processing an ECG is similarly insignificant. As a result, it is discovered that the approaches based on Kalman filter-based PLI tracking and cancellation, as well as smoother as well as extended KF [14–19], are more adaptable & stable. These analyses have considered the potential for tracking and power-line frequency variations, which are significant issues for in power systems. The Thorold frequency changes of the PLI, however, is in the range of 0.01Hz, as per power system quality standards [11, Ch. 23]. Therefore, the PLI frequency variation is relatively minimal for applications in bio signals processing. The amplitude of the PLI produced by the chosen ECG can quickly alter with sensor setup, patient position, & variations in the body volume conductor's impedance, making understanding of PLI amplitude (and phase) more crucial and limiting in such applications. Therefore, an adaptive filter without awareness of the PLI amplitude as well as phase is preferred. Here the Kalman filter gives the basic details about KF.The mathematical algorithm known as the Kalman filterthat provides a solution to the problem of optimal state estimation. It is commonly used in engineering, control systems, signal processing, and other fields where data is measured over time and subject to noise and other types of uncertainty. No presumptions are made in this investigation regarding the potential dynamics of the PLI-contaminatedbiosignals. To create a more comprehensive context for electrocardiogram denoising, the above-described dynamical models can be easily supplemented with pre-existing knowledge of the dynamics of the contaminated signals (cf. [12], [13], [14],[15]). It is further demonstrated that the approach applies to PLI with several harmonics.

In this work, there is no requirement for the prior assumption of the dynamics of ECG signals corrupted by 50 or 60 Hz PLI. However, it only depends on the ratio of noise covarianceswhich is nothing but the power factor. Hence, this dynamical model is merged with the Kalman filter, which provides more numerical stability. Further, this paper mainly focuses on -10 to -30 dB input SNR contamination with different arrhythmia ECG records.the method of denoising electrocardiogram (ECG) readings, which are recordings of the electrical activity of heart that frequently used to detect and track cardiac problems. However, a variety of noise, such as power line interference brought on by the electrical power grid, often interferes with ECG readings. Power line interference may obscure key elements of the ECG waveform, making it very difficult to that to the signal. Power line interference shows as a sinusoidal waveform at the power line frequency (generally50Hz or 60Hz) in ECG readings. ECG signals need to be eliminated of power line interference. a denoising process is typically employed. There are several methods that can be used for denoising ECG signals, including:

1. Bandstop filtering: This technique involves eliminating the power line frequency component through its ECG signal by utilizing a digital filter. Specifically, a bandstop filter is used to attenuate

frequencies around the power line frequency (e.g. 50Hz or 60Hz) while leaving other frequencies unaffected.

2. Wavelet denoising: This technique involves decomposing the ECG signal into a number of wavelet coefficients, each of which represents a distinct scale of the signal. The coefficients corresponding to the power line frequency are then removed or attenuated, and the signal is reconstructed from the remaining coefficients.

3. Independent Component Analysis (ICA): This method involves separating the ECG signal into independent components, corresponding to interference of the power line. The interference component can then be eliminated, and the ECG signal can be reconstructed from the remaining components.

4. Adaptive Filtering: This methodology uses adaptive filtering methods like RLS (“Recursive Least Squares”) or LMS (“Least Mean Squares”) algorithms to estimate the interference signal of power line by the signal of ECG. To get a denoised ECG signal, the predicted interference signal is then subtracted by the original signal.

The study concludes with the following statement: In Section 2 presents the proposed scheme with a dynamic model. Then, section 3 provides results, including data, and quantitative and qualitative measures, and in the end, the Last part of the paper is listed in this section.

Proposed Method

A**. Dynamical Model**

It is possible to assume that the single-tone PLI noise interference is made up of various sinusoids with unpredictable phase and amplitude as:

$s_n = A\cos(2pi * nf_m f_s + \phi)$ (1)

where A, f_s, n, f_m, and ϕ are stands for amplitude, sampling frequency, time index, PLI noise, and phase, respectively. In addition, by using trigonometric manipulation and adding model error parameter, Eq. (1), can be expressed as:

$s_{n+1} + s_{n-1} = 2\cos(2pi * f_m/f_s)\, s_n + \xi_n$ (2)

PLI noise, as far as can be seen, does not exhibit any rapid variations in either the phase or the amplitude. Nevertheless, including ξ_n in the model results in increased adaptability; for this reason, including ξ_n in the KF method is a desirable goal. The pure ECG damaged by PLI noise is a mixture of PLI, pure ECG, and undesired disturbance or signal and it is given by:

$y_n = s_n + w_n$ (3)

where S_n and W_n are 50 or 60 Hz PLI and zero mean an arbitrary term that represents all signals as well as noises except PLI. As this work solely considers 50 and 60 Hz PLI, it ignores the possibility that it may also contain biosignals and other disturbances. When the Eqs.(2) and (3) are transformed into the form of state-space [14] to use the KF technique, PLI noise tracking is made practicable and is given as:

$$\begin{cases} x_{n+1} = Cx_n + cg_n \\ y_n = d^T x_n + v_n \end{cases} \quad (4)$$

where $x_n = \begin{bmatrix} x_n \\ x_{n-1} \end{bmatrix}$, $C = \begin{bmatrix} 2\cos(\frac{2\pi f_0}{f_s}) & -1 \\ 1 & 0 \end{bmatrix}$, $c = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$, and $d = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$.

The above model is used to calculate PLI by applying on noisy ECG signal.

B. Kalman Filter

A mathematical process known as the Kalman filter determines the state of a dynamic system using noisy observations of that system. The prediction step and the update step make the filter's two primary components.

The prediction phase makes use of the system's state transition model to make predictions about the system's current state based on its prior state and, if applicable, any control input. The predicted state estimation is represented by $\hat{x}_k^-$, where the time index is denoted by k and the superscript - indicates that it is a prior estimate.

$\hat{x}_k^- = F_k \hat{x}_{k-1} + B_k u_{k-1}$ (5)

where:

1)F_k the matrix of state transitions, which relates the present state to the previous state; 2) $\hat{x}_{k-1}$ is the previous state estimate; 3)The control input matrix, or B_k, relates the state to the control input u; 4)At time k-1, the control input is u_{k-1}.

The error covariance matrix is denoted as P_k^- is computed during the prediction stage as well, which represents the uncertainty in the predicted state estimate:

$P_k^- = F_k P_{k-1} F_k^T + Q_k$ (6)

where:1) the error covariance matrix is P_{k-1} of the previous state estimate. 2) The state transition model's uncertainty is represented by the process noise covariance matrix, or Q_k.

The measurements and predicted state estimate are combined in the update stage to provide the updated state estimate and error covariance matrix. The updated state estimate is represented by $\hat{x}_k$, where the superscript + indicates that it is a posteriori estimate.

$$\hat{x}_k = \hat{x}_k^- + K_k(y_k - H_k\hat{x}_k^-) \quad (7)$$

Number equations consecutively. Equation numbers,

where: 1) Time k measurement is denoted by y_k.2) The observation matrix, or H_k, relates the measurements to the state. 3) The weight assigned to the predicted state estimate and the measurement in the updated state estimate are determined by the Kalman gain matrix, or K_k.

The error covariance matrix is also updated:

$$P_k = (I - K_kH_k)P_k^- \quad (8)$$

Here I is the identity matrix.

Once the dynamic model is defined, the KF is ready to apply to determining PLI, and steps are provided as follows:

Time Propagation:

$$\hat{x}_{n+1}^- = C\hat{x}_n^+$$

$$P_{n+1}^- = CP_n^+C^T + q_n cc^T \quad (9)$$

Kalman Gain:

$$H_n = \frac{P_n^- d}{d^T P_n^- d + k_n} \quad (10)$$

Measurement Propagation:

$$\hat{x}_n^+ = \hat{x}_n^- + H_n[y_n - d^T\hat{x}_n^-]$$

$$P_n^+ = P_n^- - H_n d^T P_n^- \quad (11)$$

After applying KF on noisy ECG, the PLI is tracked and then subtracted from noisy ECG and resultant signal is filtered ECG signal. This procedure is illustrated in Fig. 1.

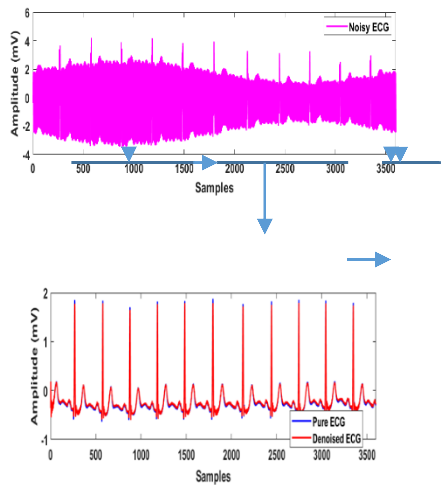


Fig. 1 Block Diagram of Denoising of 50 and 60 Hz PLI from ECG using KF.

The state space "model for a dynamic system can be expressed as:

$$x_k = F_k x_{k-1} + B_k u_k + w_k \quad (11)$$

$$y_k = H_k x_k + v_k \quad (12)$$

where:

1) The system state at time k is represented by x_k. 2) The state transition matrix, or F_k, relates the current state to the previous state. 3) x_{k-1} is the state of the system at time k-1. 4)The control input matrix, or B_k, relates the state to the control input u. 5) The control input at time k is u_k.6) The process noise, denoted by the w_k, is believed to be zero-mean Gaussian white noise with a covariance matrix. Q_k. 7) The system's measurement at time k is y_k. 8) The observation matrix, or H_k, relates the calculation to the state. 9) The measurement noise, designated by the v_k, is believed to be a zero-mean Gaussian white noise with covariance matrix R_k.

Using a prediction of the current state based on the previous state and the control input, followed by a correction based on the measurement, the Kalman filter calculates the system's state.

The prediction step is given by:

$$\hat{x}_k^- = F_k \hat{x}_{k-1} + B_k u_k \quad (13)$$

$$P_k^- = F_k P_{k-1} F_k^T + Q_k \quad (14)$$

where:

1) Given the observations up to time k-1, $\hat{x}_k^-$ is the estimated predicted state at given time k. 2) Given the data up to time k-1, P_k^- is the predicted error covariance matrix at time k. 3) Given the observations up to time k-1, $\hat{x}_{k-1}$ represents the estimated state of the system at time k-1 4) Given

the data up to time k-1, P_{k-1} is the estimated error covariance matrix at
k-1 time.
The update step is given by:

$$K_k = P_k^- H_k^T (H P_k^- H^T + R_k)^{-1} \quad (15)$$

$$\hat{x}_k = \hat{x}_k^- + K_k (y_k - H_k \hat{x}_k^-) \quad (16)$$

$$P_k = (I - K_k H_k) P_k \quad (17)$$

where:

1) K_k, or the Kalman gain matrix at time k, determines how much weight is given to the predicted state estimate and measurement is included in the updated state" estimate. 2) Given the observations up to time k, $\hat{x}_k$ represents the updated state estimate at the time k 3) P_k is the updated error covariance matrix at given time k given the observations up to time k.

The Kalman filter equations (11) to (17) are recursive, so they can be utilized to estimate the state of the system at each time step given the measurements up to that time.

The Kalman filter is a mathematical procedure that uses two steps—a prediction step and an update step—to estimate the state of a dynamic system from noisy calculation. The update step uses the measurement and the observation matrix to correct the prediction and update the estimate of the state and the error covariance matrix, while the prediction step utilizes the state transition model and the control input to predict the system's current state.

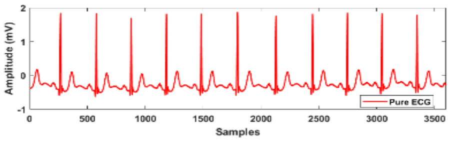
Results and Discussion

A. **Data Used**

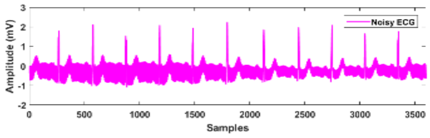
In MIT-BIH Arrhythmia Database have 48half-hour snippets of 2-channel ambulatory ECG records from the 47 individuals who took part in research conducted at the BIH Arrhythmia Laboratory throughout the period from 1975 to 1979.These individuals were recruited for the study. To ensure that less common but clinically relevant arrhythmias were represented, the remaining 25 ECG records were also drawn from the same sample. These arrhythmias were found in a collection of 4,000 24H ambulatory ECG records taken by the distinct group of patients at Boston's Beth Israel Hospital, including outpatients (40%) and inpatients (60%). The first set of twenty-three recordings was selected at random from the collection, and the second set of twenty-three recordings was also chosen at random. The recordings were digitalized throughout a range of ten millivolts at a rate of three hundred sixty times per second on each channel. Two or more than two hearts separately annotated each recording. Differences between the cardiologists' annotations were reconciled to produce computer-understandable reference annotations for each heartbeat. These annotations are included in the database and bring the total number of annotations to over 110,000. This work uses recordings of an electrocardiogram 100, 103, and 105 for denoising and filtering purposes.

B 60 Hz PLI Results

The outcomes of the ECG filtering are contrasted qualitatively using the reconstructed ECG signal after denoising and quantitatively by utilizing output SNR (Signal-To-Noise Ratio). Fig 2 provides a graphic illustration of the consequence of applying the noise reduction technique.A clean electrocardiogram is represented in Figure 2a, and a noisy signal is demonstrated in Figure 2b. The noisy ECG signal was created by combining 60 Hz PLI noise to ECG record 100 at 15dB input SNR.The entirety of the filtered findings can be seen in Figures 2c and 2d. Even though the notch filter is a powerful denoising tool, it is noticed that there is a decline in the amplitude of R-peaks for certain samples when the SNR is low (as shown in Figure 2c).Figure 2d illustrates the filtration outcome that was brought about by applying the suggested approach. It can be shown in Fig. 2d that the suggested method successfully removes 60Hz PLI noise by the ECG and closely follows the shape of the ECG signal. The outcomes taken after denoising suggest that this method performs better than the notch filter when it comes to maintaining the diagnostic information of the electrocardiogram. The quantitative examination of the output SNR values for each approach was conducted to gain deeper insight into this outcome. It is clear from looking at Table 1 that the methods under consideration produce a lower output SNR compared to the strategy that is being recommended. Comparatively, the KF has an average SNR of 15.26–24.06 dB at the output, whereas the notch filter has an average SNR of 12.34–15.41 dB at the output.



(a)



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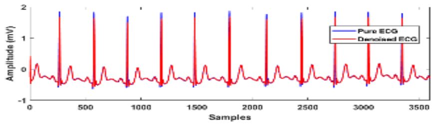
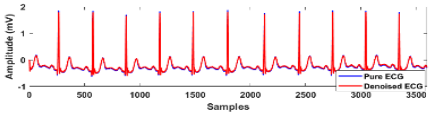


(C)

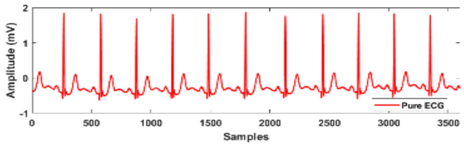


(d)

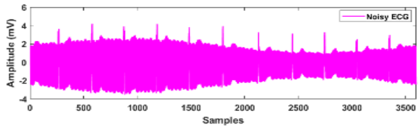
Fig. 2 60 Hz removal denoising results for ECG 100 at −15 dB. a. Clean ECG, b. noisy ECG, c. notch filter, and d. proposed.

C.50 Hz PLI Results

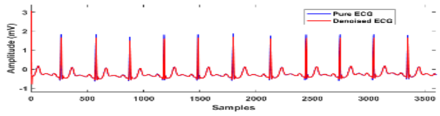
The reconstructed signal following denoising is used to contrast the filtering results qualitatively, while the output SNR is used to distinguish them quantitatively. A diagrammatic representation of the results of using the noise reduction technique is shown in Figure 3. Figure 3a depicts a clear ECG, while Figure 3b illustrates a chaotic signal. The noisy signal was produced by adding 50 Hz PLI noise at 15 dB input SNR to ECG record 100. All the filtering findings are shown in Figures 3c and 3d. Even though the notch filter is a potent denoising tool, it is seen that when the SNR is low, the R-peak amplitude for certain samples decreases (as shown in Figure 3c). This is true even if the notch filter clearly shows that 50 Hz PLI noise is present at low SNR. The filtration results produced by the suggested method are shown in Figure 3d. Fig. 3d demonstrates the suggested method successfully eliminates 50Hz PLI noise from signals of ECG and nearly mimics their structure. The denoising findings represents that this approach outperforms the notch filter in terms of preserving the electrocardiogram's content that is original or diagnostic information. A quantitative analysis of the output SNR values for each technique was conducted to explore this assertion further. Table 2 demonstrates that the other ways have a worse SNR for the output compared to the methodology being provided. The average SNR for the KF is between 20.73 and 22.07 dB, whereas the average SNR for the notch filter is between 9.61 and 11.51 dB.



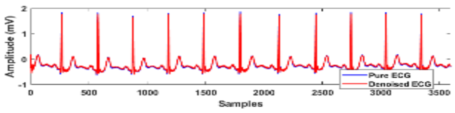
(a)



(b)



(c)



(d)

Fig. 3 50 Hz removal denoising results for ECG 100 at −15 db. a. Clean ECG, b. noisy ECG, c. notch filter, and d. proposed.

TABLE I. OUTPUT SNR FOR ECG SIGNALS 100, 103, AND 105. (60 Hz)

TABLE II. KALMAN FILTER RESULTS

Input SNR	105	103	100
-15	23.37	23.74	24.06
-20	23.29	23.66	23.69
-25	23.00	23.36	21.99
-30	21.57	21.85	15.26

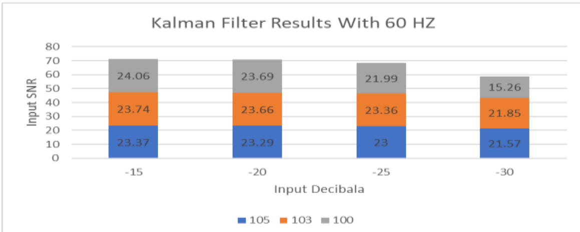


Fig 4 Graphical Representation of Kalman Filter Results

Notch Filter Results

Input SNR	105	103	100
-15	17.45	12.78	15.41
-20	16.85	12.57	15.08
-25	15.49	12.03	14.22
-30	13.01	10.75	12.34

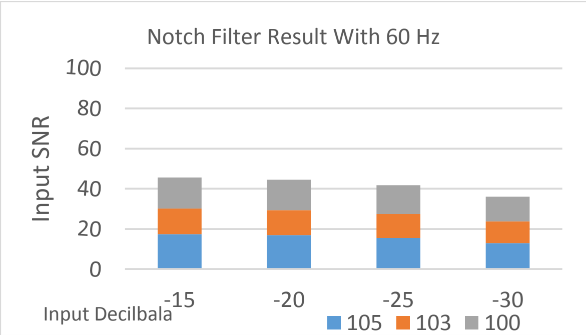


Fig 5 Graphical Representation of Notch Filter Results

TABLE III. OUTPUT SNR FOR ECG SIGNALS 100, 103, AND 105. (50 Hz)

Kalman Filter Results with 50 Hz

Input SNR	105	103	100
-15	22.13	22.07	22.00
-20	22.05	21.98	21.81
-25	21.81	21.73	20.83
-30	20.82	20.73	15.84

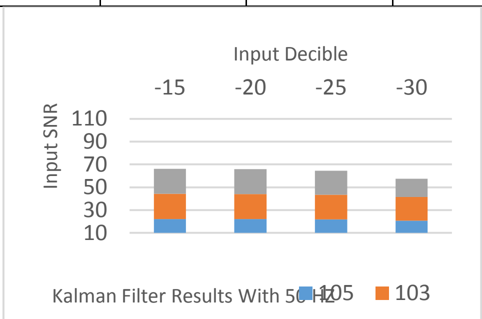


Fig: 6 Graphical Representations of Kalman FilterResults

Conclusion

Identifying and determining various human illnesses requires a phase of visual inspection of biological signals by medical professionals. For example, visual electrocardiogram (ECG) analysis may be used to detect or identify some heart diseases. The ECG is a crucial bioelectrical signal for identifying heart rhythm variations. The dynamical model and KF suggested in this study to eliminate 50 & 60 Hz PLI from ECG are presented in this paper. The KF monitors PLI to eliminate noise from the ECG signal to maintain clinical information, and the dynamical model is according to PLI data (50 or 60Hz). An arrhythmia database (ECG recordings 100, 103, and 105) with an input SNR range of -30 to -10 dB is used to evaluate the SR-CKF. The obtained output SNR (for 50 Hz: 20.82-22.13 dB and for 60 Hz: 21.85- 23.74 dB) divulges the superiority of the KF methodology while assessing it with the notch filter (for 50 Hz: 12.04-16.36 dB and for 60 Hz: 10.75-12.78 dB). The denoising of power line interference at negative SNR-contaminated electrocardiogram signals using the Kalman filter is a promising approach. The KF is an optimal state estimator that can effectively filter out noise and interference from ECG signals contaminated by power line interference. By estimating the state of the signal at each time point, the Kalman filter can improve the SNR and enhance the quality of the ECG signal. Moreover, the denoising performance of the KF is highly dependent on the tuning of its parameters, such as the measurement and process noise covariance matrices. Proper selection and tuning of these parameters are essential to achieving optimal denoising performance. In addition, the performance of the KF can be further enhanced by incorporating additional signal processing techniques, such as wavelet decomposition, to enhance the effectiveness of the filter. Overall, denoising of power line interference at negative SNR-contaminated electrocardiogram signals using the Kalman filter is a promising technique that can enhance the quality of ECG signals and aid in the accurate diagnosis and treatment of cardiac diseases.

Acknowledgment

The authors are thankful to my Supervisor, Dr.Dhanpratap
Singh, for their continued support me during writing thisconference paper. I am also thankful to my family & friendsfor their continued support during my Ph.D.

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