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RESEARCH ARTICLE

A NOVEL INTERNET OF THINGS-BASED ELECTROCARDIOGRAM DENOISING METHOD USING MEDIAN MODIFIED WEINER AND EXTENDED KALMAN FILTERS

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Abstract – The Internet of Things (IoT) offers healthcare applications that benefit customers, physicians, hospitals, and insurance companies. Wearable technology like fitness bands and other wirelessly connected gadgets like blood pressure monitors, blood glucose meters, and heart rate monitors are examples of these uses. The wearable sensor devices utilized in IoT-based Electrocardiogram (ECG) denoising systems continuously produce a huge volume of signals. IoT sensor devices produce ECG signals at a very rapid rate. As a result, the IoT-based health monitoring system generates ECG signals with very high noise levels. A clean ECG signal is needed for effective heart disease management. Imbalanced electrolytes cause an abnormal ECG reading. The noise can also cause fluctuations the ECG signals. This study shows a novel IoT-based ECG denoising method by combining two filters: the Median Modified Weiner (MMW) and the Extended Kalman filter (EKF), to overcome this issue. The characteristic of ECG signals are first subjected to the MMW filter. The extracted ECG signal is then explained with the Extended Kalman filter. MAT LAB simulates the proposed method. Root mean square error (RMSE), contrast-to-noise ratio (CNR), signal contrast, and coefficient of variation (COV) are used in the proposed MMW-EKF framework to the current systems are compared to Signal-to-noise ratio (SNR). We demonstrate how the suggested technique effectively distinguishes between various ECG signals from a noisy sample input.

Keywords *– Electrocardiogram; Internet of things; Denoising; Median Modified Weiner Filter; Extended Kalman Filter*.

1. INTRODUCTION

Patients can receive immediate treatment and return to normal activities by using remote ECG monitoring [1,2]. The ability to detect cardiac events earlier results in fewer unnecessary hospitalizations because the patient can be treated at home [3]. In the Intensive Care Unit (ICU) and the operating room, ECG monitoring is now considered standard of care [4]. It is used to identify arrhythmias and ischemia, as well as to evaluate the performance of a pacemaker/automatic implanted cardioverter-defibrillator [5,6]. In this era, it is possible to monitor the vital processes of humans using the IoT technology, regardless of where they are or what they are doing [7, 8]. Patients can monitor and control their health parameters due to the availability and advancement of IoT devices. The combined system offers the user several benefits, including detecting cardiac illness through symptoms in an emergency, transmitting messages to doctors and assisting in its treatment [9-11].

In today's world, everyone has a hectic schedule and leads a fast-paced lifestyle, which increases the risk of heart disease [12]. Cardiovascular disorders are currently the primary cause of death worldwide, emphasizing the importance of using an excellent methodology to assess a patient's cardiac health [13]. One of the most important and widely used medical instruments for heart analysis and disease diagnosis is the ECG [14]. It is a non-invasive treatment used in hospitals for measuring and diagnosing irregular cardiac rhythms. While the ECG signal is being recorded, some noise distortions can interfere [15]. Baseline drift (also known as lower frequency noise), muscle noise, electromagnetic interference and power line interference from various other devices can all cause noise in ECG readings [16,17]. As a result, one of most significant challenges in biomedicine signal processing is the extraction for pure cardio-logical indices from noisy observations, which necessitates dependable strategies to preserve diagnostic data of recorded signal [18,19].

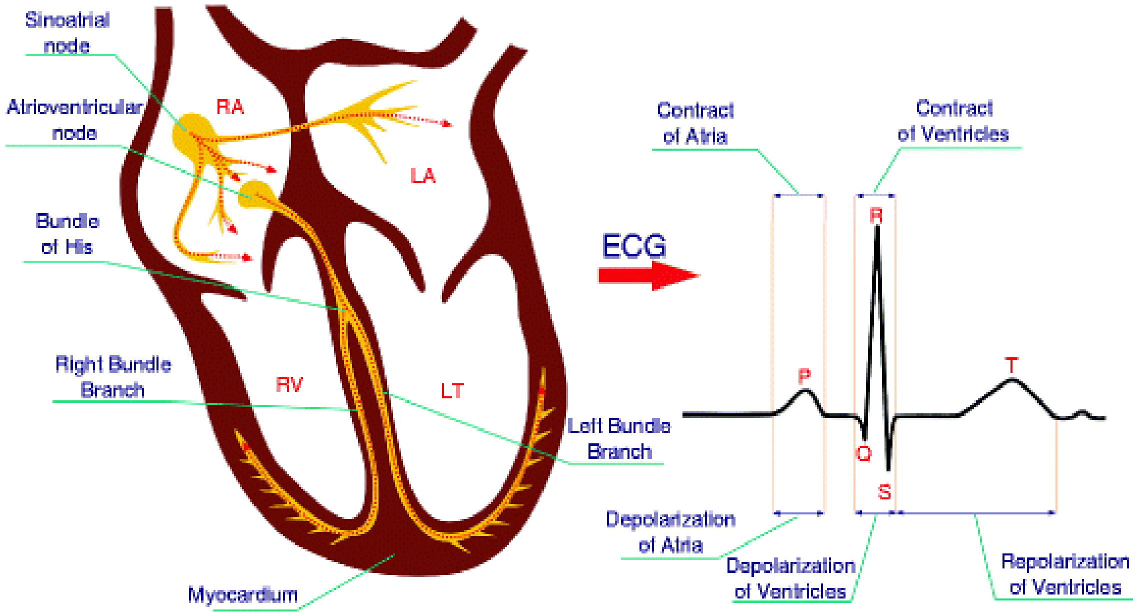


Figure 1. Typical ECG Signal [20, 21]

ECG signals have a frequency range of 0.5 to 100 Hz, and artifacts play a significant part in their processing [22]. It is made up of multiple parts, including the P wave, Q, R, and S waves (QRS) complex. Figure 1 depicts a typical ECG signal, with QRS complex representing high frequency components and T and P representing low frequency components, and any deviation in these parameters indicates the presence of heart irregularities. These waves are caused by ventricular repolarization, ventricular depolarization, and atrial depolarization in the distant field. Conventional filters are frequently employed to remove various undesirable frequency components from ECG data [23-25].

There have been several studies in recent years on ways to reduce these noises prior to disease identification and classification [26]. To remove such noises, a variety of pre-processing approaches are available. Adaptive filtering is one of the strategies for noise reduction in ECG signals, although it consumes a lot of time [27, 28]. The MMF is another common nonlinear filtering strategy for extracting tiny cardiac components from noisy ECGs, although it fails to remove Gaussian noise [29, 30]. The Wavelet Transform (WT) approach for denoising biological signals with multi-resolution characteristics, such as ECG, has gotten much interest [31]. EKF uses a linear model of the expected state with noise-corrupted observations to find the unknown state of a dynamical system. Since most systems were nonlinear, the EKF has been enhanced [32, 33]. Because of this, IoT devices' massive amounts of sensor data are not being stored using standard data processing tools and methodologies [34, 35]. Several techniques for extracting ECG components contaminated by background noise have been proposed [36]. Furthermore, the state model or measurements are unreliable in highly contaminated ECGs. These constraints push us to seek better solutions. The IoT model-based MMW-EKF algorithm has been proposed in this paper as a wiener filtering framework. Because of its nonlinear framework, the proposed algorithm outperformed other non-Gaussian non-stationary algorithms at all input SNRs. As a result, the proposed technique can completely trace the ECG signal even during periods with a lot of noise. In other words, to increase ECG denoising performance while reducing computing complexity by applying the MMW-EKF architecture. However, overall filtering performance is expected to be improved because MMW-EKF has proven to be accurate and efficient in noise removal.

This is how the rest of the study is structured. The reviews that were consulted are included in Section 2. Sections 3 present the proposed methods. Experimental and analytical results are discussed in Section 4. Section 5 discusses the conclusions of the method that has been described.

1.1. Background And Motivation

EKF is an efficient optimal estimator that provides a recursive computational technique for forecasting the state of a discrete-information controlled process from typically noisy observations while simultaneously estimating the estimates' uncertainty. It is used to decrease noise for power line interference. It is used to lessen baseline wander noise. We thoroughly reviewed ECG analysis and presented it as a stages-based process model in order to more precisely characterise and categorise the flow and importance of each phase of ECG signal processing. Considering the significant effects that effective ECG signal analysis has on both public health and the economy, we also conducted this study to provide a perspective on software and hardware instruments, as well as real-time monitoring using portable and wearable devices.

2. LITERATURE REVIEW

In 2021 Lutin et al., [37] created a learning base (QIE) was constructed and 23 photoplethysmography (PPG) datasets from the TROIKA database were studied. To the best of our knowledge, in order to improve heart rate (HR) estimate, the suggested quality engine is first tested using wrist PPG data obtained during various physical activities. When employed in combination with the cutting-edge

Wiener filtering & Phase vocoder (WFPV) method, the QIE improved HR estimate by 43% on average.

In 2021 Cheng et al., [38] proposed a novel approach for automated ECG recognition and categorization. It is used to lessen baseline wander noise. We thoroughly reviewed ECG analysis and presented it as a stages-based process model in order to more precisely characterize and categories the flow and importance of each phase of ECG signal processing. Considering the significant effects that effective ECG signal analysis has on both public health and the economy, we also conducted this study to provide a perspective on software and hardware instruments, as well as real-time monitoring using portable and wearable devices.

In 2021 Salehi and Vahidi, [39] suggested three phases and three denoising filters. I recommend three steps, three denoising filters. The Coefficient of Friction (COF) is calculated from the noise picture in the first phase. The coefficients of variation are then subjected to fuzzy c-means (FCM). The use of FCM results in the fuzzy categorization of picture areas. The three denoising filters are combined in the second stage. Fuzzy logic techniques are used in the third stage to analyze the final image. The experimental results indicate that the proposed denoising method can maintain image featurs and edges when compared to earlier despeckling techniques.

In 2022 Sarafan, et al., [40] proposed a suggested a novel method for extracting the ECG non-invasively from single-channel ECG signals using the ensemble Kalman filter (EnKF) Using the PhysioNet 2013 Challenge bank, the suggested method produces an F1 score of 97.25%, a sensitivity of 96.91%, and a minimum positive predictive value of 97.59. Our findings further demonstrate the effectiveness and dependability of the suggested strategy, which works better than earlier EKF-based algorithms.

In 2022 Tahir, et al., [41] proposed an adaptive noise cancellation (ANC) based on EKF that takes the PLI frequency into account as a different model parameter. As a result, it can follow power line interference (PLI) with a floating frequency. In recursive least squares (SSRLS) state space, filter-based PLI suppression differs from the suggested suppressor's performance. The EKF-based ANC system that is offered performs better than SSRLS-based model, according to the simulation findings. PLI is successfully removed from the ECG in each of the four cases that were examined using the RLS-based ANC approach.

In 2022 Sarafan, et al., [42] proposed the development of a new approach for denoising ECG data based on EnKF. Additional filter techniques that we analyze are the Savitzky-Golay (SG) filter, the ensemble empirical mode decomposition (EEMD), the recursive least squares (RLS) filter, the normalized least mean squares (NLMS) filter, and the total variation denoising technique. To execute. (TVD), wavelet, EKF. A noise stress test database from MIT-BIH where used. Upgraded MIT-BIH database with motion artefacts produces an average SNR of 10.96, a PRD of 150.45, and a correlation value of 0.959 using the recommended approach.

In 2023 Minh, et al., [43]. suggested a cutting-edge framework that uses data mining techniques to extract information related to diagnosing cardiac illness at the network edge while maintaining the integrity of ECG data by eliminating noise. Empirical studies demonstrate that the suggested framework increases real-time detection accuracy while preserving information integrity, in comparison to earlier approaches.

In 2023 Priyadarshini, et al., [44] proposed in order to ensure optimal energy utilization with little battery capacity, we have developed a lightweight solution that prioritizes slope amplification with real-time segmentation methods for complex QRS assessment of pulse rate. The power is provided by local computing on the node. With an enhanced frequency of 269 MHz and a power consumption of 0.7 MW, the Spartan6 FPGA on which the design was based proved perfect for real-time ECG monitoring devices.

In 2023 Cañón-Clavijo, et al., [45] presented an IoT method for monitoring ECG signals and analysing cardiac data to produce an alarm when an arrhythmia is detected. The best classification accuracy for the studied arrhythmias, according to the data, is achieved by the k-nearest neighbor method (94% for premature ventricular beats, 81% for fusion of ventricular beats, and 82% for extra sexual beats). Additionally, it can discriminate 93% and 97%, respectively, between regular and undefinable hits.

These techniques are better than earlier approaches, but they have certain shortcomings as well. Here are a few instances of aberrant ECG readings. These include: Right and left bundle branch block symptoms, premature atrial and ventricular contractions, nonspecific T-wave alterations, and ventricular hypertrophy. To overcome these drawbacks, Efficient MMW and EKF Based ECG Denoising techniques has been proposed.

3. PROPOSED MMW-EKF ALGORITHM

In this paper proposed a novel Efficient MMW-EKF Based ECG Denoising Method has been proposed. The MMWF algorithm is employed to preprocess the noisy ECG signal. As stated, the MMWF estimation uses the signal's characteristic to denoise it. The partially denoised ECG signal is subsequently processed using the EKF approach to solve that problem. To denoise the ECG dynamic signal obtained after MMWF, the EKF discretized it. Finally, the ECG signal is reconstructed by combining all of the EKFs. As a result, the noises' harmful effects were significantly reduced. In Figure 2, a block diagram depicts the proposed method, which successfully combines MMW-EKF methodologies.

This section describes our proposed ECG denoising method in detail. First, the MMW filters is applied to the characteristic ECG signal. The EKF is then utilized to describe the method for extracting the ECG signal from noise.

This approach can maintain the edge signals while the noise distribution is reduced. The following is how the MMWF algorithm is calculated:

$$h_{mmwf}\ (x, y) = \hat{\delta} + \frac{\sigma^2 - u^2}{\sigma^2}[a(x, y) - \hat{\delta}] \quad (1)$$

where $\hat{\delta}$ is the median value's size, σ^2 and u^2 are the signal's Gaussian noise variance and the noise variation, respectively, and *a (x, y)* is the amplitude at the time (x, y).

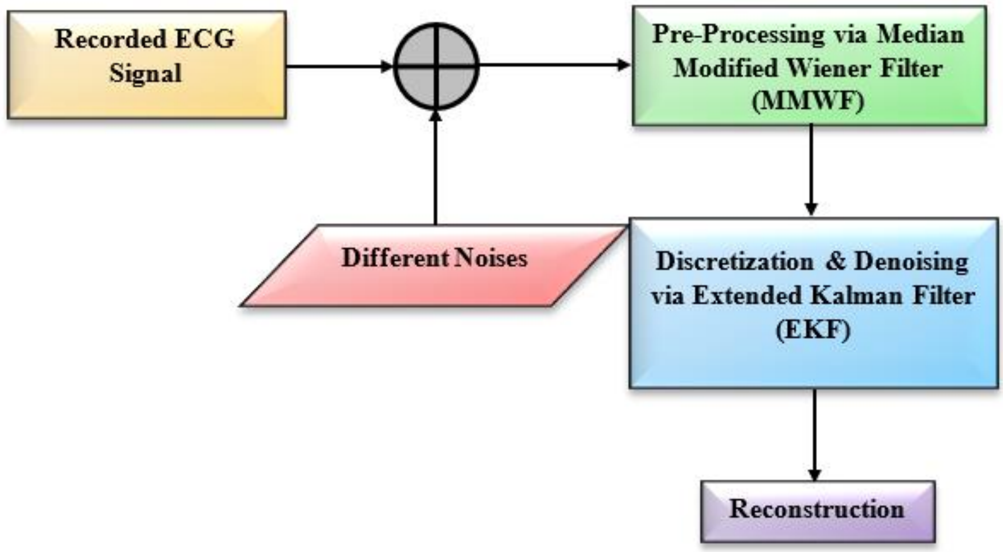


Figure 2. Denoising of ECGs: Overall Proposed Architecture

3.1. MMWF Algorithm: ECG Signal Characteristics

The MMWF approach is employed to lessen the distribution of noise in ECG signal. The background area of a deteriorated signal is denoised using the median filter to enhance signal quality. Additionally, the Wiener filter (WF) is generally employed in this method to maintain the edge signal. The MMWF method, which is based on the WF, decreases noise in the deteriorated signal by replacing the values of the mask matrix with the median values. The WF is represented as follows in the r ×t sized mask matrix:

$$\mu = \frac{1}{rt}\sum_{r,t\in a} n(r, t)$$

$$\sigma^2 = \frac{1}{rt}\sum_{r,t\in a} n^2(r, t) - \mu^2$$

Where, μ is the mean, σ^2 is the variance of Gaussian noise in the signal, r × t is the size of the neighborhood area an in the mask, and n (r, t) represents each value in the area a.

Thus, the MMWF is represented as follows:

$$k_{mmwf}(r, t) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}(b(r, t)) - \mu)$$

where v^2 is the mask WF matrix's noise variance setting.

The MMWF technique has the benefit of enhancing the poor signal quality in the following ways: Comparing the drop-off effect to the median and Wiener filter approaches, the edge signal is better retained. In conclusion, the MMWF approach performs better than traditional filters in terms of denoising effect and can keep the edge information while removing the background noise signal.

3.1.1. Evaluation of Quality

ECG signals are analyzed by MMWF, and reconstructed signals were acquired. The CNR, COV, and SNR linked to noise are analyzed.

The degree of dispersion around the mean is inversely correlated with the COV. It is frequently stated as a percentage. [46,47] It enables for the comparison of value distributions with disparate measurement scales because it lacks units. The strength of the signal is contrasted with the strength of the noise in a SNR. Decibels are most frequently used to express it (dB). Higher numbers often denote a better specification since there is a greater ratio of valuable information (the signal) to undesired data (the noise). CNR is similar to the metric SNR.

Because COV and CNR are derived using a single region's signal and variance values, they were employed for noise level analysis. Furthermore, the CNR was used to calculate the signal difference between two neighboring regions' variance values while also taking noise and contrast into account.

$$COV = \frac{\sigma_X}{\delta} \quad (2)$$

$$SNR = \frac{S_X}{\sigma_X} \quad (3)$$

$$CNR = \frac{|S_X - S_Y|}{\sqrt{\sigma^2{}_X + \sigma^2{}_Y}} \quad (4)$$

The Return on Investment (ROI's) average standard deviation and signal intensity are S_X and σ_X, respectively, whereas the background region's average standard deviation and signal intensity are S_X and σ_X. The ROI is used to mould the image compression to one particular area of compression. Instead of reducing all the pixel intensities we are using ROI to specify the required arrangements.

In addition, for the purpose of determining the loss of high-frequency signals caused by MMWF technique, signal similarity was evaluated with reference to noise-free signals. Applied the following parameters for this evaluation: RMSE, cubic centimetre (CC) and Peak Signal Noise Ratio (PSNR):

$$RMSE=\sqrt{\frac{\sum_{i=1}^{N}(r_i - c_i)^2}{N}} \quad (5)$$

$$PSNR = 10(\frac{S_{max}{}^2}{RMSE^2}) \quad (6)$$

The reference and comparison signals are represented by r_i and c_i, respectively, and $S_{max}{}^2$ is maximum signal intensity in ROI.

$$CC=\frac{\sum_{i=1}^{N}(r_i - \hat{r})(c_i - \hat{c})}{\sqrt{\sum_{i=1}^{N}(r_i - \hat{r})^2}\sqrt{\sum_{i=1}^{N}(c_i - \hat{c})^2}} \quad (7)$$

The $\hat{c}$ and $\hat{r}$ represents the average values of comparison and reference signals.

The signal loss is induced by MMWF smoothing can be assessed using PSNR and RMSE, which quantitatively show the signal difference. COV, CNR and SNR linked to noise was analyzed to evaluate MMWF's noise reduction efficiency from the obtained signals, allowing overall quality of signal to be evaluated. Thus, characteristics of ECG signal are evaluated.

3.2. EKF To Train MMWF for ECG Denoising (MMW-EKF)

The EKF is utilized to denoise the ECG signal once the parameters have been analyzed. Since the nonlinear dynamic ECG model Eqn. (5), (6), and (7) are continuous time, and the EKF is a discrete-time technique, continuous nonlinear dynamic ECG model Eqn. (5), (6), and (7) must be discretized. A first-order numerical method called the Euler methods, often referred to as the forward Euler methods, is used to resolve ordinary differential equations (ODEs) with a specified beginning value. Euler method is used to discrete Eqn. (5), (6), and (7). As a result, the discrete form of (7) will be:

$$a(u+1) = (1+\rho h)a(u) - \omega h b(u)$$

$$b(u+1) = (1+\rho h)b(u) + \omega h a(u)$$

$$c(u+1) = -\sum_{j\epsilon\{P,Q,R,S,T\}} \frac{a_j}{{b_j}^2} h\Delta\theta_j \; exp\, exp\left(-\frac{\Delta\theta_j^2}{2b_j^2}\right) - ((h-1)c(u) - hc_0) \quad (8)$$

where h is the sampling time.

The following is a more compact rewrite of the nonlinear discrete ECG model (26):

$$X_{u+1} = f(X_u) \quad (9)$$

where X_u is the state vector, and it is represented by X_u = $[a_u \; b_u \; c_u]^T$.

$$\begin{pmatrix} a(u+1) \\ b(u+1) \end{pmatrix} = \begin{matrix} (1+\rho h)a(u) - \omega h b(u) \\ (1+\rho h)b(u) + \omega h a(u) \end{matrix}$$

$$c(u+1) - \sum_{j\epsilon\{P,Q,R,S,T\}} \frac{a_j}{{b_j}^2} h\Delta\theta_j \; exp\, exp\left(-\frac{\Delta\theta_j^2}{2b_j^2}\right) - ((h1)c(u) - hc_0) \quad (10)$$

The state equation of the discrete ECG model without noise is represented by the vector equation (28). We need to introduce some random sounds in (27) to simulate a more realistic ECG signal:

$$X_{u+1} = f(X_u, r_u) \quad (11)$$

where $r_u = [r_1, r_2, r_3]^T$ state noise is an additive random vector that is normal and Gaussian with a zero mean, then (28) can be written as:

$$\begin{pmatrix} a(u+1) \\ b(u+1) \\ c(u+1) \end{pmatrix} = \begin{pmatrix} (1+\rho h)a(u) - \omega h b(u) + r_1(u) \\ (1+\rho h)b(u) + \omega h a(u) + r_2(u) \\ -\sum_{j\epsilon\{P,Q,R,S,T\}} \frac{a_j}{{b_j}^2} h\Delta\theta_j exp exp\left(-\frac{\Delta\theta_j^2}{2b_j^2}\right) - ((h-1)c(u) - hc_0) + r_1(u) \end{pmatrix} \quad (12)$$

The state vector $X_u = [a_u \; b_u \; c_u]^T$ can be connected to the measurement equation corresponding to state space representation (29) by the following relation:

$$b_u = g\,(X_u, m_u)$$
$$= [0\;0\;1]\; X_u + m_u \quad (13)$$

m_u is measurement noise and y_u is the considered measure.

A linear approximation of (30) is required to use EKF (see (2) and (3)). To compute the Jacobian matrices entries (see (3)), arrange (30) and (31) as follows:

$$\begin{cases} a(u+1) & X\,(a(u), b(u), c(u), r_1(u)) \\ b(u+1) = & Y\,(a(u), b(u), c(u), r_2(u)) \\ c(u+1) & Z\,(a(u), b(u), c(u), r_3(u)) \end{cases} \quad (14)$$

$$b_u = g\,(X_u, m_u) \quad (15)$$

The entries of the Jacobian matrix A_k are then calculated.

$$\frac{\partial X}{\partial a} = 1 + h - \left(\frac{2ha(u)^2 + hb(u)^2}{\sqrt{a(u)^2 + b\,(u)^2}}\right)$$

$$\frac{\partial X}{\partial b} = -\frac{ha(u)b(u)}{\sqrt{a(u)^2 + b(u)^2}} - \omega h \frac{\partial X}{\partial c} = 0$$

$$\frac{\partial Y}{\partial a} = -\frac{ha(u)b(u)}{\sqrt{a(u)^2 + b(u)^2}} + \omega h$$

$$\frac{\partial Y}{\partial b} = 1 + h - \left(\frac{ha(u)^2 + 2hb(u)^2}{\sqrt{a(u)^2 + b(u)^2}}\right) \frac{\partial Y}{\partial c} = 0$$

$$\frac{\partial Z}{\partial a} = \sum_{j\epsilon\{P,Q,R,S,T\}} \frac{\frac{a_{j\omega}}{{b_j}^2} hy(u)}{a(u)^2 + b(u)^2} exp\, exp\left(-\frac{\Delta\theta_j^2}{2b_j^2}\right) - [\,1 - \frac{\Delta\theta_j^2}{b_j^2}] \quad (16)$$

$$\frac{\partial Z}{\partial y} = \sum_{j\epsilon\{P,Q,R,S,T\}} \frac{-\frac{a_{j\omega}}{{b_j}^2} hx(u)}{x(u)^2 + y(u)^2} exp\, exp\left(-\frac{\Delta\theta_j^2}{2b_j^2}\right) - [\,1 - \frac{\Delta\theta_j^2}{b_j^2}]$$

$$\frac{\partial Z}{\partial z} = 1 - h$$

$$\frac{\partial X}{\partial r_1} = \frac{\partial Y}{\partial r_2} = \frac{\partial Z}{\partial r_3} = 1$$

$$\frac{\partial X}{\partial r_2} = \frac{\partial X}{\partial r_3} = \frac{\partial Y}{\partial r_1} = \frac{\partial Y}{\partial r_3} = \frac{\partial Z}{\partial r_1} = \frac{\partial Z}{\partial r_2} = 0$$

$$\frac{\partial g}{\partial x} = \frac{\partial g}{\partial y} = 0; \frac{\partial g}{\partial z} = 1 - h; \frac{\partial g}{\partial m} = 1$$

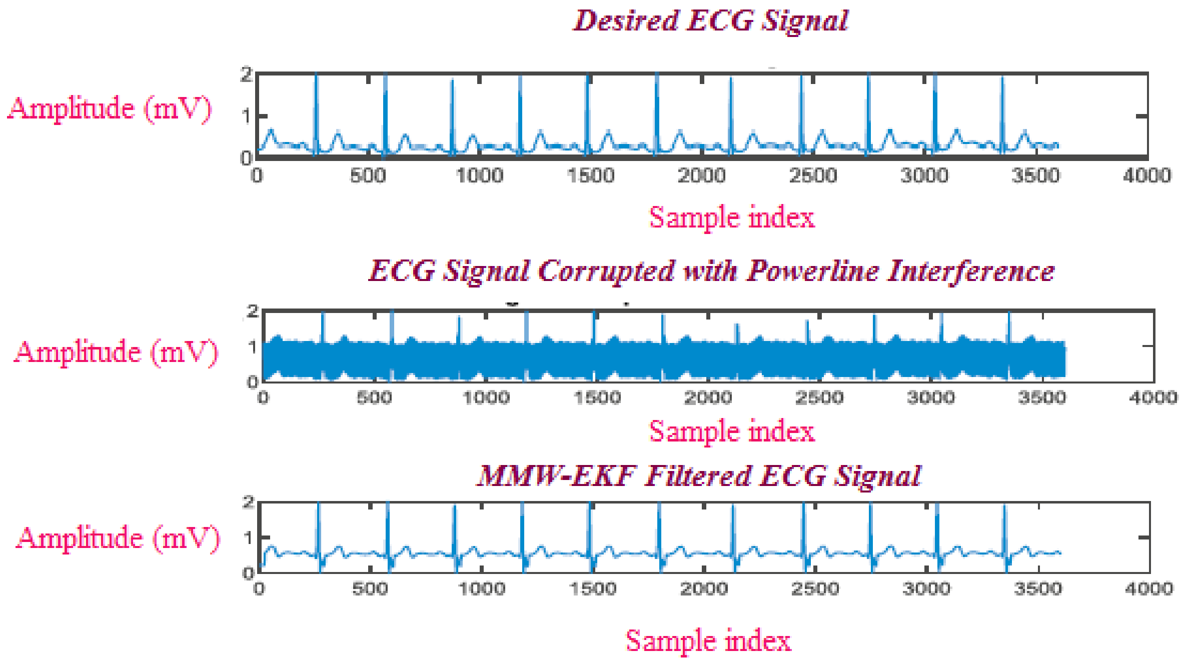
For noise removal, the proposal utilizes the (Enterprise data management) EDM implementation. However, our method constructs an MMW-EKF filter using the dynamical set of equations, which uses the state dynamics and ECG as an observation. As a result, the proposed MMW-EKF technique for ECG denoising is an efficient.

4. RESULT AND DISCUSSION

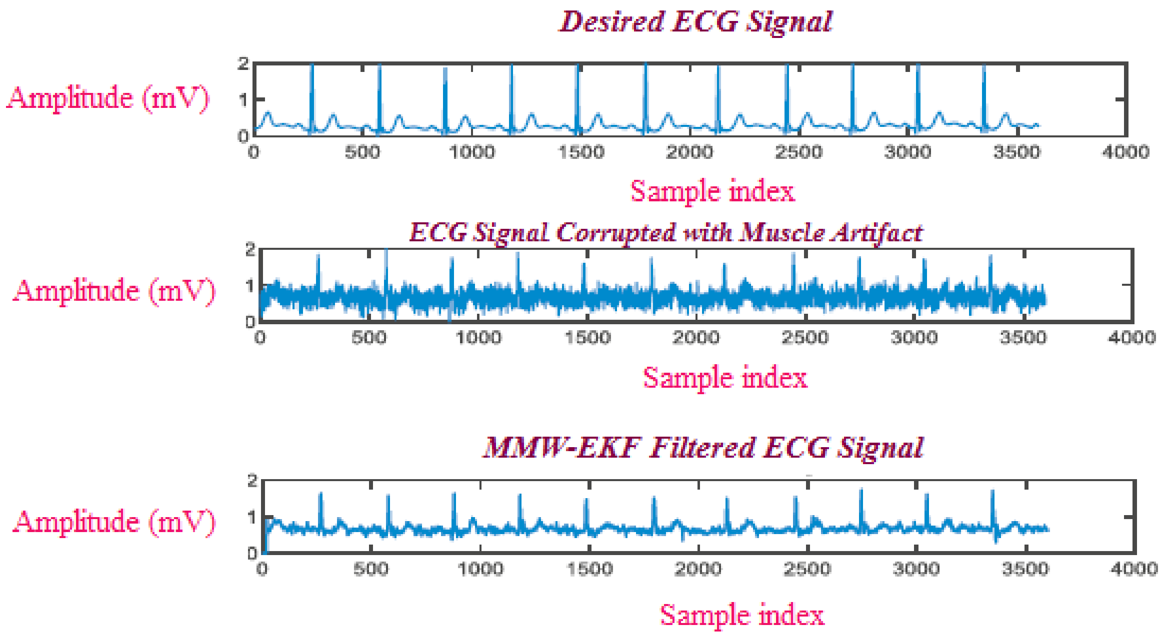
The experimental arrangement of the proposed MMM-EKF technique based denoised was implemented using MATLAB. A comparison of the proposed MMM-EKF technique Performance with some filters they are Gaussian Filter (GF), Median Filter (MF) and CF is made. The proposed MMW-EKF based on ECG denoising is simulated in this section using MATLAB. Figure 3 depicts the filter outputs.

Datasets

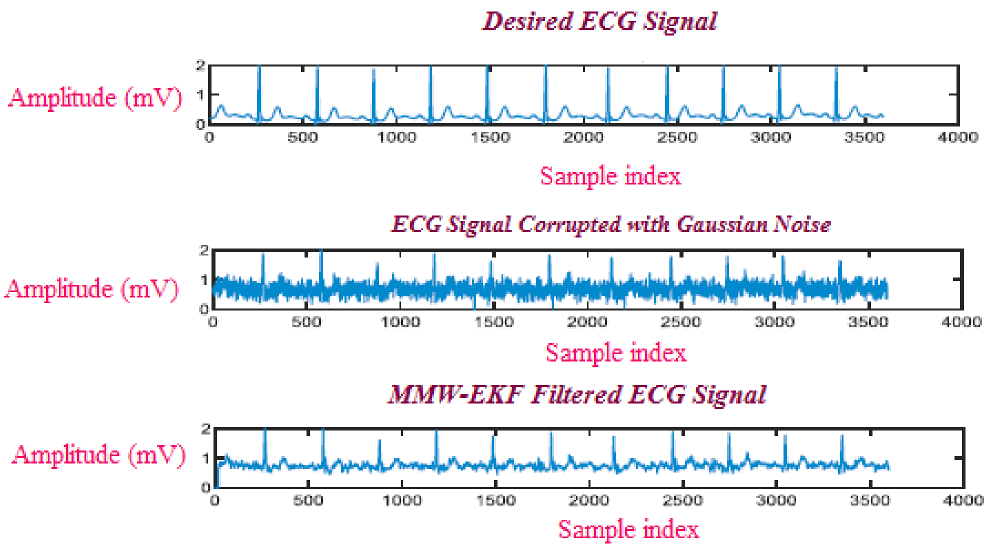
A distinct clinical ECG dataset that has been optimized for machine learning computers is the PTB-XL database. 21,837 clinical 12-lead ECGs, each lasting 10 seconds and recorded at 500 Hz and 100 Hz with 16-bit resolution, are included in the PTB-XL ECG dataset. These ECGs are from 18,885 different people.



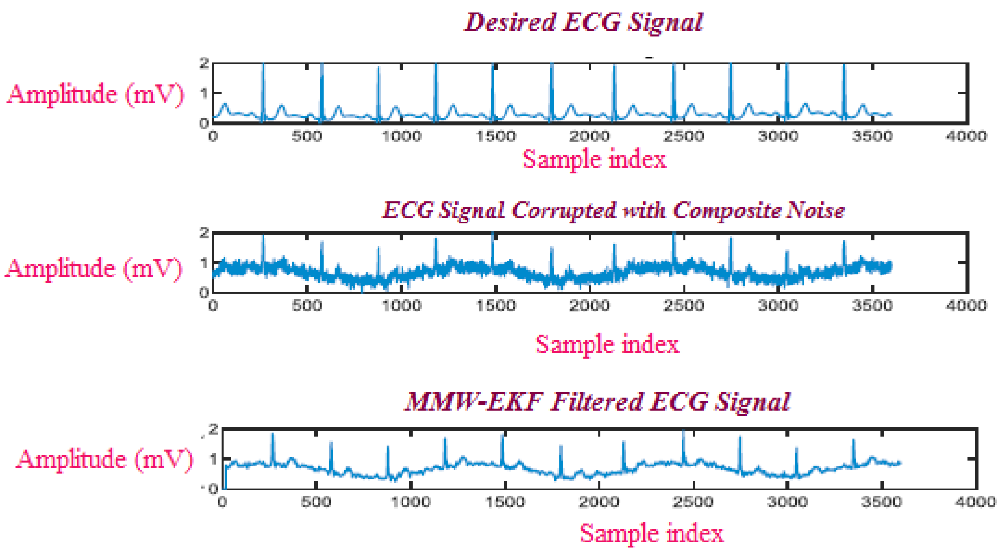
a) Power line Interference



b) Muscle artefact



c) Gaussian noise



d) Composite noise

Figure 3. Graphical Illustration for a Denoised ECG Signal using the Median Modified Wiener and Extended Kalman Filters with Various Noises

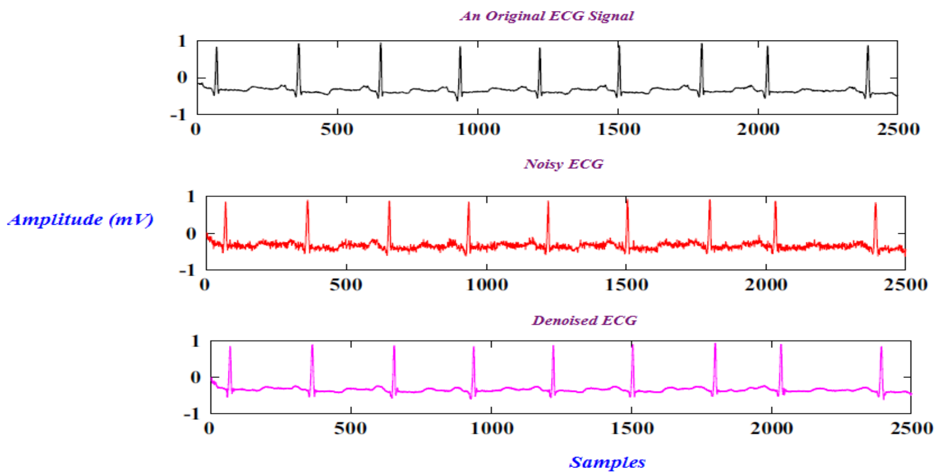


Figure 4. Proposed Method for a Denoised Signal

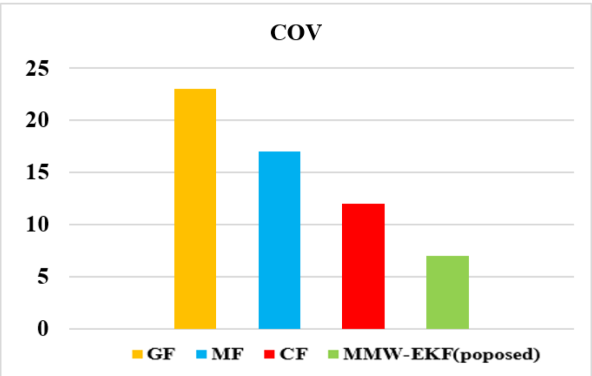
Figure 4 displays the original, clean ECG signal, the noisy variations in the signal, and the denoised signal produced by the suggested technique. With a 10dB input SNR, the graphs exhibited database record number 100 in the MMW-EKF.

When comparing the Kalman, Wiener, and proposed MMW-EKF filters to various data sets, SNR and RMSE were determined for each data set. Our proposed approach has a greater SNR and a lower RMSE (see Table 1).

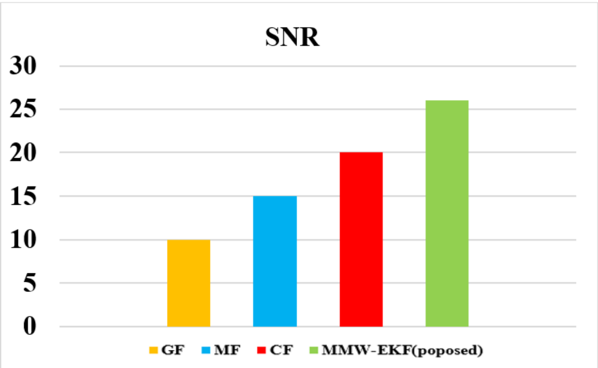
Table 1. Different noise has different values for various performance parameter

SIGNAL EXPECTATION									
Noises	**Filters**	**SNR**				**RMSE**			
		Data 103	**Data 105**	**Data 121**	**Average**	**Data 103**	**Data 105**	**Data 121**	**Average**
PI	WF	6.985	6.435	9.245	7.565	0.062	0.132	0.051	0.072
	KF	4.773	5.435	6.422	5.546	0.165	0.156	0.115	0.143
	MMW-EKF	7.123	6.945	9.545	7.856	0.051	0.111	0.021	0.0371
Gaussian	WF	5.352	5.986	8.216	6.593	0.122	0.148	0.073	0.121
	KF	4.455	5.255	6.768	5.458	0.221	0.186	0.144	0.184
	MMW-EKF	5.455	6.203	8.521	6.956	0.101	0.122	0.055	0.026
Muscle Artifact	WF	6.846	5.344	8.979	7.048	0.073	0.185	0.056	0.102
	KF	5.321	5.236	7.426	6.012	0.131	0.162	0.093	0.142
	MMW-EKF	7.235	5.682	9.235	7.3315	0.052	0.098	0.045	0.065
Composite	WF	6.435	4.911	7.347	6.247	0.063	0.234	0.095	0.142
	KF	4.726	5.188	6.325	5.349	0.160	0.163	0.152	0.159
	MMW-EKF	6.985	5.356	7.563	6.5641	0.044	0.132	0.054	0.084

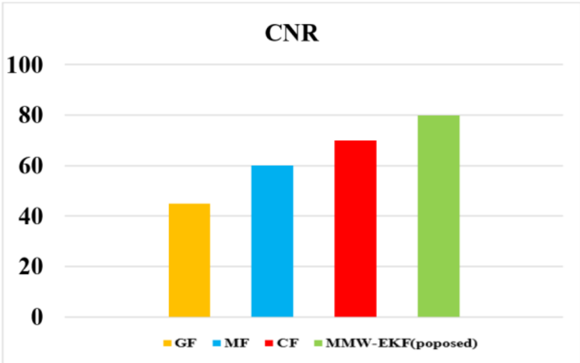
The CNR, COV and SNR, were calculated to compare the noise levels of the MMW-EKF applied signal to the original signal and other existing approaches. Over the original signal and several existing approaches, the CNR, COV and SNR values of the MMW-EKF reconstructed signal are increased by factors of 2.01, 1.02, and 1.60, respectively (see Figure 5).



a) COV



b) SNR



c) CNR

Figure 5. Comparison between the Original Signal and the Signal Reconstructed with MMW-EKF

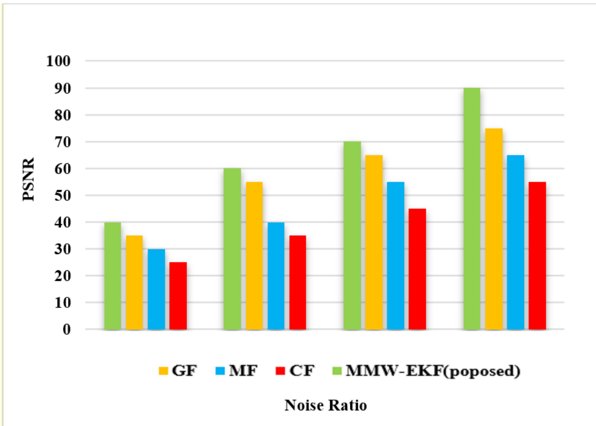


Figure 6. Measures of PSNR

Our results indicate that the MMW-EKF can successfully reduce noise from ECG signals. Furthermore, the sample should be optimized for signal loss and noise level to improve MMW-EKF efficiency. Measures of PSNR is shown in Figure 6.

The PSNR between two images - the actual image and its noisy approximation - is used to describe noise. The maximum pixel value for 8-bit pictures is 255. PSNR values for image compression are often in the 30 to 50 dB range.

5. CONCLUSION

The MMW-EKF were used in this paper to design an IoT based ECG denoising process that allowed advantage of the denoising features of each filter. The proposed technique denoises a noisy signal by preprocessing it and estimated the signal's characteristics with the MMW filter. To further decrease the effects of additive noise, the partially denoised ECG signal is analyzed and discretized using an EKF. The performance of parameters such as COV, SNR, and CNR is also analyzed in the simulation results. The analysis of this research confirms the proposed method's suitable for filtering noisy ECG signals. In the event of a sudden illness, the terminal will also have the ability to collect data for processing and notify the patient's family of a data transfer. To reduce distortion and boost system reliability, additional work entails adding baseline variation to the EDM.

CONFLICTS OF INTEREST

The writers say they have no competing interests.

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REFERENCES

[1] G.J. Lakshmi, M. Ghonge and A.J. Obaid, "Cloud based Iot smart healthcare system for remote patient monitoring", *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 7, no. 28, pp. e 4-e4, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Y. Feng and Z. Pan, "Optimization of remote public medical emergency management system with low delay based on internet of things", *Journal of Healthcare Engineering*, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] G. Boriani, F. Guerra, R. De Ponti, A. D'Onofrio, M. Accogli, M. Bertini, G. Bisignani, G.B. Forleo, M. Landolina, C. Lavalle and P. Notarstefano, "Five waves of COVID-19 pandemic in Italy: Results of a national survey evaluating the impact on activities related to arrhythmias, pacing, and electrophysiology promoted by AIAC (Italian Association of Arrhythmology and Cardiac Pacing)", *Internal and Emergency Medicine*, vol. 18, no. 1, pp. 137-149, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] M.C. Perez-Guzman, E. Duggan, S. Gibanica, S. Cardona, A. Corujo-Rodriguez, A. Faloye, M. Halkos, G.E. Umpierrez, L. Peng, G.M. Davis and F.J. Pasquel, "Continuous glucose monitoring in the operating room and cardiac intensive care unit". *Diabetes Care*, vol. 44, no. 3, pp. e50-e52, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[5] C. Li, X. Hu and L. Zhang, "The IoT-based heart disease monitoring system for pervasive healthcare service", *Procedia computer science*, vol. 112, pp. 2328-2334, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[6] M. Bianco, S. Breviario, T. Fraccalini, R. Ferri, C. Biolè, P. Destefains, G. Varalda, A. Boccuzzi and A. Chinaglia, "Epilepsy and syncope-A case report and narrative review of arrhythmias connected to temporal lobe epilepsy", *Journal of Electrocardiology*, vol. 73, pp.76-78, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] A.K.M. Majumder, Y.A. ElSaadany, R. Young and D.R. Ucci. "An energy efficient wearable smart IoT system to predict cardiac arrest", *Advances in Human-Computer Interaction*, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[8] Naji, Hassan Saadallah, and Hanan Badeea Ahmed, "Design and Analysis of a Signal Denoising and Estimation System", *In IOP Conference Series: Materials Science and Engineering*, vol. 1067, no. 1, pp. 012145. IOP Publishing, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[9] Hesar, Hamed Danandeh, and Maryam 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, 2017.[CrossRef] [Google Scholar] [Publisher Link]

[10] K. Azbeg, O. Ouchetto and S.J. Andaloussi, "BlockMedCare: A healthcare system based on IoT, Blockchain and IPFS for data management security", *Egyptian Informatics Journal*, vol. 23, no. 2, pp.329-343, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] N.Y. Philip, J.J. Rodrigues, H. Wang, S.J. Fong and J. Chen. "Internet of Things for in-home health monitoring systems: Current advances, challenges and future directions", *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 2, pp. 300-310, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] B. R. Manju and M. R. Sneha. "ECG denoising using wiener filter and kalman filter." *Procedia Computer Science*, vol. 171, pp. 273-281, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[13] S. Gaamouri, M. Bousbia Salah, and R. Hamdi. "Denoising ECG signals by using extended kalman filter to train multi-layer perceptron neural network", *Automatic Control and Computer Sciences*, vol. 52, no. 6, pp. 528-538, 2018[CrossRef] [Google Scholar] [Publisher Link]

[14] McSharry, E. Patrick Gari D. Clifford, Lionel Tarassenko, and Leonard A. Smith, "A dynamical model for generating synthetic electrocardiogram signals", *IEEE transactions on biomedical engineering*, vol. 50, no. 3, pp. 289-294, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[15] Lahmiri, Salim, and Mounir Boukadoum, "Hybrid Wiener and partial differential equations filter for biomedical image denoising", *In 2016 14th IEEE International New Circuits and Systems Conference (NEWCAS)*, IEEE, pp. 1-4, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[16] A. Turnip, M. Turnip, A. Dharma, D. Paninsari, T. Nababan and C.N. Ginting, "An application of modified filter algorithm fetal electrocardiogram signals with various subjects", *International Journal of Artificial Intelligence*, vol. 18, no. 1, pp.207-217, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[17] Kaur, Harjeet, and Rajni. "A novel approach for denoising electrocardiogram signal using hybrid technique", *Journal of Engineering Science and Technology*, vol. 12, no. 7, pp. 1780-1791, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[18] R.S. Chandel, S. Sharma, Kaur, S., Singh, S. and R. Kumar, "Smart watches: A review of evolution in bio-medical sector", *Materials Today: Proceedings*, vol. 50, pp.1053-1066, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] Ouali, Mohammed Assam, Kheireddine Chafaa, Mouna Ghanai, Louis Moreno Lorente, and Dolores Blanco Rojas. "ECG denoising using extended Kalman filter", *In 2013 International Conference on Computer Applications Technology (ICCAT)*, pp. 1-6. IEEE, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[20] J. Duan, Q. Wang, B. Zhang, C. Liu, C. Li and L. Wang, "Accurate detection of atrial fibrillation events with RR intervals from ECG signals", *Plos one*, vol. 17, no. 8, pp. e0271596, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] A. Ukil, L. Marin, S.C. Mukhopadhyay and A.J. Jara. "AFSense-ECG: Atrial fibrillation condition sensing from single lead electrocardiogram (ECG) signals", *IEEE Sensors Journal*, vol. 22, no. 12, pp. 12269-12277, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] N. Keskes, S. Fakhfakh, O. Kanoun and N. Derbel. "Representativeness consideration in the selection of classification algorithms for the ECG signal quality assessment", *Biomedical Signal Processing and Control*, vol. 76, p.103686, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[23] A. Mishra, and S. Bhusnur, "A New Adaptive Modeling and Denoising of Real ECG signal", *In 2022 IEEE 3rd Global Conference for Advancement in Technology (GCAT)* IEEE, pp. 1-6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] D.U. Uguz, Z.T. Canbaz, C.H. Antink, M. Lüken and S. Leonhardt, "A novel sensor design for amplitude modulated measurement of capacitive ECG", *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1-10, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[25] V.A. Ardeti, V.R. Kolluru, G.T. Varghese and R.K. Patjoshi. "An Overview on State-of-the-Art Electrocardiogram Signal Processing Methods: Traditional to AI-Based Approaches", *Expert Systems with Applications*, pp. 119561, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Yazdanpanah, Babak, G. S. N. Raju, and K. Sravan Kumar, "Reduction Noise of ECG Signal Using Extended Kalman Filter", *International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)*, vol. 3, no. 9, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[27] D. Liu, H. Zhao, X. He and L. Zhou, "Polynomial constraint generalized maximum correntropy normalized subband adaptive filter algorithm", *Circuits, Systems, and Signal Processing*, pp.1-18, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[28] Khazraj, Hesam, F. Faria Da Silva and Claus Leth Bak, "A performance comparison between extended Kalman Filter and unscented Kalman Filter in power system dynamic state estimation", *In 2016 51st International Universities Power Engineering Conference (UPEC)*, pp. 1-6. IEEE, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[29] V. Ramakrishnan and P. Pete, "Weighted Median filtering-based fusion of multiple exposure images for HDRI. D. J, Weighted Median filtering-based fusion of multiple exposure images for HDRI", April 9, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[30] Bakhshande, Fateme, and Dirk Söffker, "Adaptive Step Size Control of Extended/Unscented Kalman Filter Using Event Handling Concept", *Frontiers in Mechanical Engineering*, vol. 5, no. 74, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[31] Kulikov, Gennady Yu, and Maria V. Kulikova, "Practical implementation of extended Kalman filtering in chemical systems with sparse measurements", *Russian Journal of Numerical Analysis and Mathematical Modelling*, vol. 33, no. 1, pp. 41-53, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[32] Zhao, Junbo, Marcos Netto and Lamine Mili, "A robust iterated extended Kalman filter for power system dynamic state estimation", *IEEE Transactions on Power Systems*, vol. 32, no. 4, pp. 3205-3216, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[33] Becerra, Victor Manuel, P. D. Roberts and G. W. Griffiths. "Applying the extended Kalman filter to systems described by nonlinear differential-algebraic equations", *Control Engineering Practice*, vol. 9, no. 3, pp. 267-281, 2001. [CrossRef] [Google Scholar] [Publisher Link]

[34] Gustafsson, Fredrik, and Gustaf Hendeby, "Some relations between extended and unscented Kalman filters", *IEEE Transactions on Signal Processing*, vol. 60, no. 2, pp. 545-555, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[35] Y. Zhong, L. Chen, C. Dan and A. Rezaeipanah, "A systematic survey of data mining and big data analysis in internet of things," *The Journal of Supercomputing*, pp. 1-49, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[36] Shamsollahi, Mohammad Bagher. "ECG denoising and compression using a modified extended Kalman filter structure", *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 9, pp. 2240-2248, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[37] E. Lutin, D. Biswas, N. Simões-Capela, C. Van Hoof and N. Van Helleputte, "Learning based Quality Indicator Aiding Heart Rate Estimation in Wrist-Worn PPG", *In 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* IEEE, pp. 7063-7067, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[38] J. Cheng, Q. Zou and Y. Zhao, "ECG signal classification based on deep CNN and BiLSTM", *BMC medical informatics and decision making*, vol. 21, pp.1-12, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[39] H. Salehi and J. Vahidi, "A novel hybrid filter for image despeckling based on improved adaptive wiener filter, bilateral filter and wavelet filter". *International Journal of Image and Graphics*, vol. 21, no. 03, pp. 2150036, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[40] S. Sarafan, T. Le, M.P. Lau, A. Hameed, T. Ghirmai and H. Cao, "Fetal electrocardiogram extraction from the mother's abdominal signal using the ensemble kalman filter", *Sensors*, vol. 22, no. 7, p.2788, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[41] S. Tahir, M.M. Raja, N. Razzaq, A. Mirza, W.Z. Khan, S.W. Kim and Y.B. Zikria, "Extended Kalman Filter-Based power line interference canceller for electrocardiogram signal", *Big Data*, 10(1), pp. 34-53, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[42] S. Sarafan, H. Vuong, D. Jilani, S. Malhotra, M.P. Lau, M. Vishwanath, T. Ghirmai, and H. Cao, "A novel ecg denoising scheme using the ensemble kalman filter", *In 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 2005-2008, IEEE, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[43] Q.T. Minh, P.H. Phung and P.N. Huu. "Fog-Enabled IoT Framework for Heart Disease Diagnosis Systems", *Journal of Mobile Multimedia*, pp. 389-418, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[44] R. Priyadarshini, N. Shaikh, R.K. Godi, P.K. Dhal, R. Sharma and Y. Perwej, "IOT-based power control systems framework for healthcare applications", *Measurement: Sensors*, vol. 25, pp.100660, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[45] R.E. Cañón-Clavijo, C.E. Montenegro-Marin, P.A. Gaona-Garcia and J. Ortiz-Guzmán. "IoT Based System for Heart Monitoring and Arrhythmia Detection Using Machine Learning", *Journal of Healthcare Engineering*, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[46] K. Madurakavi and I, J.R., "Assessing nitrogen dioxide (NO2) impact on health pre-and post-COVID-19 pandemic using IoT in India", *International Journal of Pervasive Computing and Communications*, vol. 18, no. 5, pp. 476-484, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[47] V. Gomathy, K. Janarthanan, F. Al-Turjman, R. Sitharthan, M. Rajesh, K. Vengatesan and T.P. Reshma, "Investigating the spread of coronavirus disease via edge-AI and air pollution correlation", *ACM Transactions on Internet Technology*, vol. 21, no. 4, pp. 1-10, 2021. [CrossRef] [Google Scholar] [Publisher Link]

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