Filters for Electrocardiogram Signal Processing: A Review

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Abstract. Recording an Electrocardiogram (ECG) signal is a difficult task in the field of biomedical engineering. The ECG signal reflects the electrical activity of the heart muscle and is important in diagnosing heart conditions. However, the signal is often contaminated with various types of noise during processing, such as muscle noise, power line interference, baseline wandering, and motion artifacts. It is crucial to separate the desired signal from these noise sources to ensure accurate diagnosis. This article examines the challenges associated with ECG preprocessing filters in the last five years.

Keywords: ECG · Filter · Signal processing

1 Introduction

The outputs from biosensors are analog signals, which are sent to the analog processing and digital conversion block. There, the signals are amplified, filtered, conditioned, and converted to digital form. The signal that is often used in these modifications is the electrocardiogram (ECG). In the simultaneous contraction of both ventricles blood is forced from the heart into the pulmonary artery from the right ventricle and into the aorta from the left ventricle. The electrocardiogram is an electrical measure of the sum of these ionic changes within the heart.

Throughout the data acquisition procedure, it is critical that the information and structure of the original biological signal of interest as faithfully preserved. ECG data is later processed to determine arrhythmic activity and other important diagnostic characteristics. ECG signals are essential to diagnose and analyze cardiac disease, because ECG signals record the cardiac electrical activity, which conveys important pathological information about the human heart's condition. By analyzing the characteristics of ECG, doctors are able to judge whether the heart situation is normal or not, and know what troubles the heart confronts with. Since these signals are often used to aid the diagnosis of pathological disorders, the procedures of amplification, analog filtering or A/D conversion should not generate misleading or untraceable distortions. Distortions in a signal measurement could lead to a delay in the initiation of appropriate medical treatment or to an improper diagnosis. An ECG typically contains unwanted interference or noise. Such interference has the detrimental effect of obscuring relevant information that may

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be available in the measured signal. Interference noise occurs when unwanted signals are introduced into the system by outside sources. It is introduced by power lines (50 or 60 Hz), fluorescent lights, AM/FM radio broadcasts, computer clock oscillators, laboratory equipment, cellular phones, and so forth. Even the action potentials from nerve conduction in the patient generate noise at the sensor/amplifier interface. Also, ECG measurements from the heart can be affected by bioelectric activity from adjacent muscles. A measurement ECG electrode can pick up extraneous signals from the muscles, lungs, and even from the internal electronics of the recording devices.

An ECG has very small magnitudes, approximately in the millivolts. Filters are often used to remove noise from a signal, typically through the use of frequency-domain analysis to design the filter. Appropriate filtering allows one to clean up the signal, thus improving its quality of signal and the diagnostic reliability in clinical settings. Noise filtering is the fundamental step in the processing of the ECG signal. Alternating current (AC) source from a power supply introduces the PLI noise, which is a major noise to be removed at the initial stage of processing steps. Based upon the country region, the signal has a frequency of about 50/60 Hz. The main reasons behind such type of noise are the stray effect of alternating current field because of loops in the electricity wires, disengaged electrodes, electromagnetic interference due to power supply, improper grounding of ECG equipment, or heavy current load due to other equipment in the room. A low-frequency noise called baseline wander noise also occurs during ECG recording. It has the range of 0.15 to 0.3 Hz. This noise occurs due to the breathing process of that person and forces the ECG signals to shift in the baseline. The other probable causes may be due to the movement of cables during the recording of the ECG signal or due to unclean lead electrodes/wires, or due to loosen electrode connection. In addition to the heart, muscle contraction contributes to the electromyogram (EMG) noise due to depolarization and repolarization waves generated from muscle contraction near the electrodes. Another type of noise is contact noise. It is caused by the heart's position in relation to the electrode's variance. Electrode–skin impedance variation is the mechanism responsible for baseline disturbances. An artifact called electrode motion artifact occurs due to the movement of electrodes. The subject's vibrations, movement, or breathing usually contribute to motion artifacts. Due to very slow fluctuations in the impedance of the skin electrode, a baseline drift arises at a very low frequency in the ECG signal. This noise cannot be disposed of, but high-quality hardware and a cautious circuit plan can very well reduce it. The main reasons are the connection of electrodes, wires, signal processor/amplifier, and ADC. At the hospitals, nurses and doctors do not pay attention to electrode placement. It results in common mode noise, and therefore 50 Hz filtering must be used.

This work attempts to summarize filtering methods and approaches into a complete overview and categorize them into a systemic taxonomy. Therefore, the purpose of this paper is to review the latest achievements in this field in the last 5 years.

2 Methods

The aim of this review paper was to provide an analysis of filters used for electrocardiogram (ECG) signal processing. A literature search was conducted in multiple databases, including PubMed, Scopus, IEEE Xplore, and Web of Science, using relevant search terms and keywords such as ECG, signal processing and filter. The search was limited to studies published in English and the search was conducted within the last 5 years. The studies identified in the search were screened based on predefined inclusion and exclusion criteria. Studies were included if they described the use of filters in ECG signal processing, and were published in peer-reviewed journals, conference proceedings, or books. Studies were excluded if they did not meet the inclusion criteria or were published in a language other than English. Data was extracted from each study, including the type of filter used, the characteristics of the ECG signals processed, the performance metrics used to evaluate the filter, and the main findings of the study. The extracted data was organized by themes, The themes included the different types of filters used in ECG signal processing. The extracted data was critically analyzed to identify patterns and trends in the literature, and to draw conclusions about the effectiveness of different types of filters for ECG signal processing.

Overall, the methods (Table 1) used in this review paper were designed to provide a rigorous and systematic approach to the literature review process, and to ensure that the analysis was comprehensive, accurate, and unbiased.

3 Results

In the study conducted by Venkatesan et al. (2018) [8], author utilized a standardized Least Mean Squares (LMS) adaptive filter with a delayed error in the preprocessing stage to achieve higher speed and a low-latency design with fewer elements, mainly to remove white noise. The results were compared with second-order IIR notch filter (Tables 2 and 3).

Huang, Hui, Shiyan Hu, and Ye Sun (2019) [4] considered a new low-distortion adaptive Savitzky-Golay (LDASG) filtering method for ECG denoising based on discrete curvature estimation (see Fig. 1).

With comparable noise elimination performance, the standard SG filter has greater distortions at high variation parts, especially at R peaks, than the proposed method. The proposed method is compared with the EMD-wavelet-based method and the non-local means (NLM) denoising method in terms of both noise elimination and signal distortion reduction. For signal distortion reduction, their method outperforms the EMD-wavelet method by reducing MSE by 33.33% and PRD by 18.25%, and outperforms the NLM method by reducing MSE by 50% and PRD by 25.24% (Tables 4 and 5).

Table 1. A brief overview of the considered filters.

Filter/method	Purpose	Comment
The least mean square (LMS) adaptive filter	Removes white noise	The higher speed and a low-latency design
Low-distortion adaptive Savitzky-Golay (LDASG)	Denoises high signal variations with low signal distortion	The remarkable performance of data smoothing
Wavelet without applying thresholding	Identifies the ECG and noise frequency range for zeroing wavelet detail coefficients in the subbands with no ECG coefficients in the frequency content	More accurate algorithm with a more efficient estimation of baseline
Combined EMD method	Efficiently removes a pure 50 Hz sinusoidal noise termed as power line interference	The better improvement in SNR values of the signal
Adaptive wavelet thresholding method (AWT)	A new shrinkage function depending on the identical correlation is utilized to realize smooth transition from the thresholding cutoff to a real wavelet coefficient	The distinctadaptability in the selections of base wavelet, threshold and shrinkage function
DWT with the β-hill climbing	Finds the optimal wavelet parameters that will minimize the mean square error (MSE) between the original and denoised signals	The mean square error is minimised
Bayesian denoising framework	Credited to ECG denoising, segmentation and arrhythmia detection	An adaptive particle weighting strategy. Helpful algorithm, especially in removing baseline drifts caused by MA noises
Synchro-squeezed wavelet transform (SSWT)	Uses for baseline wander correction and powerline interference reduction in electrocardiogram (ECG) signals using empirical wavelet transform (EWT)	A significant improvement in output signal-to-noise ratio

(*continued*)

The author Jain et al. (2018) [2] designed a robust system for ECG denoising, incorporating EMD algorithm with fractional integral filtering by "Riegmann Liouvelle (RL) and Savitzky–Golay (SG)." It is proved from the results that the EEMD-PSO and EEMD-CS methods give the best performance for denoising attaining maximum SNR and minimum MSE for all types of noises (Table 6).

Table 1. (*continued*)

Filter/method	Purpose	Comment
EMD with SWT and a mean based filter	Uses the features of EMD as well as that of the SWT and NLM filter to efficiently remove a pure 50 Hz sinusoidal noise termed as power line interference	Noticeably enhanced the SNR value of the ECG signals
Switching Kalman filter	Extracts fiducial points of ECG signals	The better performance in noisy environments
Kalman filter	Estimates the underlying signal and removes noise and artifacts from the recorded ECG signal	Applicable only for linear systems
Wiener filter	Estimates the optimal filter coefficients for each sample of the signal	The mean square error is minimised
Adaptive notch filters with sharp resolution	Eliminates signals from the stop band. Eliminates PLI	The specific freq. range and only one eliminated noise at a time

Table 2. Performance analysis of ECG records using second-order IIR notch filter.

Record	SNR_{input}	SNR_{output}	$SNR_{improved}$	MSE	RMSE	NMSE	PRD
100	23.35	58.89	33.53	1.0211	1.0105	2.10×10^{-7}	4.58×10^{-6}
102	19.98	51.41	31.46	1.2233	1.1060	5.09×10^{-7}	7.13×10^{-6}
105	23.41	58.26	34.84	2.0429	1.4293	3.81×10^{-7}	6.17×10^{-6}
111	20.25	57.66	37.41	0.6868	0.8251	4.54×10^{-7}	6.74×10^{-6}
115	23.08	58.01	34.93	3.8366	1.9587	3.16×10^{-7}	5.62×10^{-6}

To eliminate the white Gaussian noise in the ECG signals. Alyasseri et al. (2017) [28] have suggested combining the DWT with the β-hill climbing technique for suppressing the white Gaussian noise in the ECG signals.

Hesar and Mohebbi (2017) [29] have proposed the model based Bayesian denoising framework, which utilizes the DWT based thresholding with the Variational Mode Decomposition (VMD) to lower the noise impact on the ECG signals and then adopts the Marginalized Particle-Extended Kalman Filter (MP-EKF) with the Fuzzy Based

Table 3. Performance analysis of different ECG records using adaptive LMS filter.

Record	SNR_{input}	SNR_{output}	$SNR_{improved}$	MSE	RMSE	NMSE	PRD
100	23.35	55.34	29.98	0.0226	0.1503	1.83×10^{-4}	1.35×10^{-4}
102	19.98	49.08	29.09	0.0063	0.0797	1.04×10^{-4}	1.02×10^{-4}
105	23.41	56.72	33.31	0.0379	0.1948	2.76×10^{-4}	1.66×10^{-4}
111	20.25	48.89	28.64	0.0015	0.0385	3.91×10^{-5}	6.62×10^{-5}
115	23.08	52.29	29.21	0.6189	0.7867	1.9×10^{-3}	4.41×10^{-4}

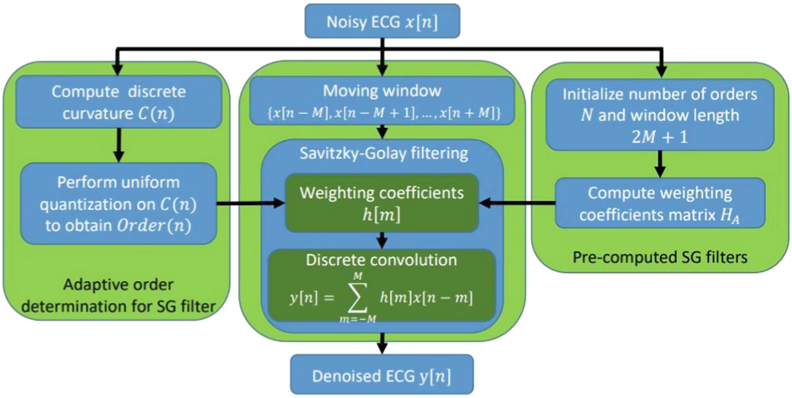

Fig. 1. Diagram of the proposed LDASG filter for ECG signal denoising.

Adaptive Particle Weighting (FBAPW) technique to further tackle the noises in the signals.

Singh and Sunkaria (2017) [30] have made use of the EWT with the technique of mode subtraction for dealing with different kinds of noises in the ECG signals. Synchro-Squeezed Wavelet Transform (SSWT) can also realize the adaptive time-frequency decomposition, which is the goal of EMD.

Oliveira et al. (2018) [5] found approach to be superior to normal threshold and notch filtering techniques in removing power-line interference.

A new phenomenon called adaptive wavelet thresholding method (AWT) was designed in the paper by He and Tan (2018) [27] for the ECG signal enhancement. By means of cross-relation coefficient and entropy energy relation, the best base wavelet was generated for ECG signal filtering automatically.

S. A. Malik, S. A. Parah and G. M. Bhat (2021) [31] concluded that combined denoising capabilities of classical EMD method provided a better improvement in SNR

Table 4. Results of ECG denoising performance with the SNR level of 0 dB.

ECG records	SNR improvement			MSE			PRD (%)		
	EMD-w	NLM	LDASG	EMD-w	NLM	LDASG	EMD-w	NLM	LDASG
#101	9.5	9.05	10.47	0.015	0.017	0.012	33.48	35.29	29.96
#103	7.16	7.83	10.35	0.029	0.026	0.014	43.87	40.61	30.37
#104	8.85	7.79	10.39	0.016	0.021	0.011	36.09	40.88	30.21
#105	9.71	8.22	10.78	0.015	0.022	0.011	32.71	38.83	28.91
#106	6.79	6.16	9.45	0.041	0.048	0.022	45.73	49.23	33.69
#115	8.06	7.29	9.17	0.015	0.061	0.039	39.55	43.16	34.78
#117	13.85	11.24	14.91	0.031	0.056	0.024	20.28	27.41	17.98
Average	9.13	8.23	10.79	0.03	0.04	0.02	35.96	39.34	29.41

Table 5. Comparison of the computation time of different methods (seconds).

ECG records	EMD-Wavelet	NLM	LDASG
#101	0.792	0.490	0.550
#103	0.730	0.490	0.531
#104	0.767	0509	0.583
#105	0.815	0.469	0.582
#106	0.754	0.507	0.459
#115	0.789	0.507	0.569
#117	0.779	0.474	0.622
Average	0.775	0.492	0.556

Table 6. Comparison of EMD with fractional integral filtering with other related methods.

Method	Random noise		Gaussian noise		PLI noise	
	SNR (dB)	MSE	SNR (dB)	MSE	SNR (d)	MSE
EMD	23.35	27.72	2.37	1.55×10^{-4}	0.0125	1.34×10^{-3}
EMD-norm-2	8.7892	0.002	6.8665	0.0032	6.355	0.0035
EEMD-GA	8.7892	0.002	5.8147	0.004	9.4462	0.0017
EEMD-CS	10.0809	0.0015	7.97	0.0024	9.4673	0.0017
EEMD-PSO	10.0809	0.0015	7.9776	0.0024	9.4673	0.0017

values of the signal in comparison to the method involving only EMD or wavelet based method. The clinical features are preserved and ECG was not compromised (Table 7).

Table 7. Considered different wavelet transforms.

Researches	Filter/method	Noise	Results (signal #100)
A. Alyasseri, A. Khader, A. Al-Betar, and L. M. Abualigah	β-Hill climbing algorithm and wavelet transform	WGN	$SNR_{in} = 0$ dB $SNR_{out} = 8.9649$ dB
H. D. Hesar and M. Mohebbi	Soft thresholding based on VDM + EKF	WGN	$SNR_{in} = -1$ dB $SNR_{out} = 1.395 \pm 0.539$ dB
O. Singh and R. K. Sunkaria	EWT with mode subtraction	PLI BW	$SNR_{in} = 0$ dB $SNR_{out} = 0.9943$ dB $SNR_{in} = 0$ dB $SNR_{out} = 16.4016$ dB
Oliveira, Bruno Rodrigues de, et al.	A wavelet-based method without applying thresholding techniques	PLI	$SNR_{imp\ (avg)} = 40.7086$ dB
He H and Tan Y	Adaptive wavelet thresholding	PLI, BW and muscle artifact	The AWT has obtained the lowest re and modest values of SNR and RMSE
S. A. Malik, S. A. Parah and G. M Bhat	EMD with SWT and a mean based filter	PLI	$SNR_{in} = 0$ dB $SNR_{IMP} = 10.74$ dB

Akhbari, Mahsa, et al. (2018) [13] presents a new approach for extracting fiducial points (FPs) of ECG signals by using a switching Kalman filter (SKF). The proposed method is compared with methods based on wavelet transform. For the proposed method, the mean error and the root mean square error across all FPs are 2 ms (i.e. less than one sample) and 14 ms, respectively. The standard deviations are around four to five samples for the onset and offset of waves and around one sample for the peak of waves. The errors and the standard deviation and RMSE values for the SKF are significantly smaller than those obtained using other methods (Table 8).

Authors Manju, B. R., and M. R. Sneha (2020) [10] concluded that the Wiener filter is a method of denoising a signal that involves using the spectral properties of the signal and the noise (Fig. 2).

The results indicate that the Wiener filter (Fig. 3) produces a higher SNR value, low MSE, and low PRD compared to the Kalman filter (Fig. 2) for all types of noise. The simulation results have shown that Wiener filter is a better filtering technique than Kalman filter in terms of SNR, PSD, MSE, PRD. The inefficient performance of the Kalman filter is due to its restricted application to non-linear systems (Table 9).

Chen, Binqiang, et al. (2019) [11] focuses on eliminating PLI from ECG and proposes an Adaptive Notch Filter with Sharp Resolution (ANFwSR) that do not require any

Table 8. Mean ± standard deviation (first line) and RMSE (second line) of error in ms between FPs and manual annotations for signals of the QT database ($f_s = 250$Hz).

	P_{on}	P_{on}	P_{on}	QRS_{on}	R_{peak}	QRS_{off}	T_{peak}	T_{off}
SKF	23.4 ± 15.2 27.8	−0.1 ± 1.5 1.5	−6.4 ± 20 21	6.6 ± 10.2 12	0.01 ± 0.1 0.1	−5.7 ± 8.5 10.3	−0.01 ± 0.4 0.4	0.6 ± 10.8 10.8
Wavelet	−2.3 ± 31.6 31.7	0.7 ± 25 25	2.6 ± 15.2 15.4	12.4 ± 13.6 18.4	1.4 ± 3.6 3.8	1.9 ± 13.8 13.9	7.5 ± 27.5 28.5	7.3 ± 32.2 33

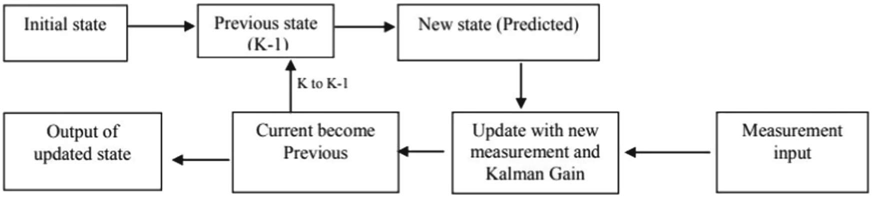

Fig. 2. Block diagram of Kalman filter.

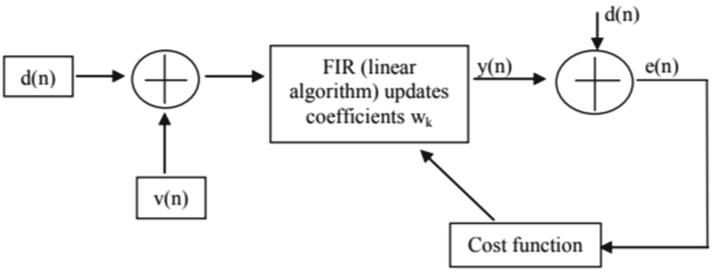

Fig. 3. Block diagram of Wiener filter.

specified parameters, making the algorithm easier to implement. ANF is better than conventional notch filters because ANF does not only reduce unwanted effects but also preserves QRS-complex features in the filtered signal. The compared results found that the ANF has the smallest maximal value and RMS value of construction errors among the three methods, indicating an improved SNR in the filtered signal (Table 10).

Table 9. Values of various parameters for different noises using Kalman and Wiener filter.

Noises	Filters	Estimated signal											
		SNR				MSE				PRD			
		Data	Data	Data	Average	Data	Data	Data	Average	Data	Data	Data	Average
Gaussian	Weiner	5.3435	5.9737	8.2075	6.5083	0.1343	0.1422	0.0649	0.1138	74_384	65.958	45.492	61.94
	Kalman	4.4499	5.2543	6.7547	5.4363	0.2171	0.1916	0.1239	0.1775	89.03	74.850	58.439	74.106
Power line interference	Weiner	6.9821	6.4314	9.2382	7.5505	0.0741	0.1255	0.0480	0.08253	57.026	61.694	39.436	52.718
	Kalman	4.7660	5.4244	6.4117	5.5340	0.1510	0.1434	0.1242	0.1395	80.89	69.733	60.351	70.324
Muscle arti fact	Weiner	6.9001	5.3253	8.9682	7.0645	0.0683	0.1971	0.0492	0.1048	56.615	74.624	40.452	57.230
	Kalman	5.3188	5.2970	7.4177	6.0111	0.1292	0.1863	0.0929	0.1361	74.109	74.152	52.178	66.813
Baseline wander	Weiner	4.8079	4.8212	5.8269	5.152	0.1763	0.2270	0.1731	0.1921	82.574	80.823	67.861	77.086
	Kalman	3.3259	3.7172	4.4944	3.8458	0.2758	0.2869	0.3083	0.2903	107.49	96.086	86.603	96.726
Composite noise	Weiner	6.4427	4.9244	7.3395	6.2355	0.0799	0.2337	0.0965	0.1367	60.790	80.254	52.918	64.654
	Kalman	4.4744	5.1929	6.3193	5.3288	0.1560	0.1766	0.1462	0.1596	81546	74.267	62.736	72.849

Table 10. Comparisons between the ANFwSR and two types of IIR notch filters.

	The proposed method	The conventional IIR filter		The improved IIR filter	
		Entire signal	Ringing part	Entire signal	Ringing part
Maximal error	1.1601	9.0063	6.0187	370.58	310.58
RMSE	0.4436	1.8412	1.0015	60.7558	60.9910

4 Conclusion

A review of denoising techniques has been conducted in this paper. The paper demonstrates how the filters and transformations play a crucial role in eliminating noise and enhancing the input ECG signal. Starting from the notch filter, where only one particular noise frequency (50 Hz) was removed at a time efficiently, but instantly failed when there was a variation in frequency of noise. Hence, the adaptive filter was introduced in order to overcome such drawbacks. In the end, it turned out that by looking at the research based on the last five years, wavelets are the most represented. Overall, these studies demonstrate ongoing research into improving the effectiveness of filters in ECG signal processing, with new and innovative techniques being developed to address specific challenges and improve the quality of ECG measurements.

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