©2025 Published in 11th International Symposium on Intelligent Technologies in Engineering and Science 16-18 May 2025 (ISITES2025 Diyarbakır - Turkey)

A Performance Comparison Between Traditional Filtering and Modern Decomposition Methods in ECG Signal Denoising

Çiğdem Gülüzar ALTINTOP
Department of Biomedical Engineering, Faculty of Engineering, Erciyes University, Turkey

Abstract

This study investigates the effectiveness of three filtering methods—Butterworth IIR filter, Empirical Mode Decomposition (EMD), and Variational Mode Decomposition (VMD)—for noise removal from ECG signals across 17 arrhythmia classes using the MIT-BIH Arrhythmia Database. The methods were evaluated using statistical metrics, including correlation coefficient, Mean Square Error (MSE), and Signal-to-Noise Ratio (SNR). The results demonstrate that VMD outperforms the other methods with the highest correlation (0.9838), the lowest MSE (0.0005), and the highest SNR (25.2979), indicating its superior ability to preserve signal quality and remove noise effectively. The EMD method exhibited the lowest performance with higher MSE and lower SNR. This study highlights the potential of VMD as a reliable and consistent signal processing technique for ECG analysis.

Key words: ECG denoising, Variational Mode Decomposition, Empirical Mode Decomposition, signal quality assessment, biomedical signal processing

1. Introduction

Electrocardiography (ECG) is the process of recording the heart's electrical activity. ECG is produced as a result of the sum of the depolarization potentials of millions of cardiac cells and provides information about the functioning of the heart [1].

A normal ECG signal consists of P, Q, R, S, and T waves representing certain parts of the heartbeat. These waves' amplitudes, durations, and regularities are essential in diagnosing arrhythmias (heart rhythm disorders). Arrhythmia is a heart condition resulting from abnormal electrical activity of the heart. Different arrhythmias usually occur in the heart with various mechanisms, and each requires a different treatment approach [2]. Arrhythmia diagnosis is traditionally made by the clinician or physician manually calculating and examining components such as amplitude, duration, and frequency. However, it is both time-consuming and laborious to make the correct diagnosis. For this reason, there are many studies in the literature for automatic arrhythmia detection [3, 4]. Studies generally consist of feature extraction and classification stages. In order to extract features that will achieve successful results, purifying the noisy ECG signal from noise is important.

ECG signals are critical for identifying fatal arrhythmias as they can cause sudden cardiac death. Still, they are frequently affected by noise, including electromyographic (EMG) noise, power line

*Corresponding author: Address: Faculty of Engineering, Department of Biomedical Engineering Erciyes University, Kayseri, TURKEY. E-mail address: cigdemacer@erciyes.edu.tr, Phone: +90352-207-66-66/ Ext. No: 32989

interference (PLI), motion artifacts, and baseline wander. Filtering techniques improve the quality of ECG signals by minimizing noise while keeping the distinctive waves.

For this reason, many methods have been used to filter ECG signals, and the best filtering method is still being investigated. In particular, the methods used in the studies are Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) Filters [5], Butterworth filters [6], Wavelet Transform-Based Techniques (DWT [7], EWT [8]), deep learning approach [9], and Empirical Mode Decomposition (EMD) [10]. Each filtration technique has certain limitations. While FIR filters increase the computational load due to their high order requirement, IIR filters cannot maintain phase accuracy and carry the risk of instability. The wide passband of Butterworth filters is a disadvantage for applications requiring sharp frequency separation. Wavelet-based methods (DWT, EWT) are dependent on the selection of the appropriate wavelet function in terms of frequency resolution. Deep learning approaches have limitations due to the large data requirement and high computational costs. The EMD method has limitations due to the uncertainties in the mixing and separation process between modes. In contrast, Variational Mode Decomposition (VMD) provides a more stable, parametrically controllable, and theoretically more robust signal decomposition by optimizing each mode around a specific bandwidth and separating it simultaneously [11]. Therefore, this study compares the three most preferred methods (IIR filter, EMD, and VMD) for noise elimination of ECG signals from 17 different arrhythmia groups (MIT-BIH Arrhythmia Database).

2. Dataset

ECG signals were obtained from PhysioNet and the MIT-BIH Arrhythmia Database. The data can be accessed with open access at "https://data.mendeley.com/datasets/7dybx7wyfn/3" [12]. The database contains ECG signals from 45 patients. ECG signals consist of 17 classes in total, including normal sinus rhythm, pacemaker rhythm, and 15 different arrhythmias. The amount of data for 17 classes is given in Table 1. See the references for the expansion and detailed explanation of the arrhythmias in the data [13].

Table 1. Data amount for each class

NSR	*APB*	*AFL*	*AFIB*	*SVTA*	*WPW*	*PVC*	*Bigeminy*	*Trigeminy*	*VT*	*IVR*	*VFL*	*Fusion*	*LBBB*	*RBBB*	*SDHB*	*PR*
283	66	20	135	13	21	133	55	13	10	10	10	11	103	62	10	45

As seen in Table 1, the ECG rhythms and cardiac abnormalities considered in this study include: Normal Sinus Rhythm (NSR), Atrial Premature Beat (APB), Atrial Flutter (AFL), Atrial Fibrillation (AFIB), Supraventricular Tachycardia (SVTA), Wolff-Parkinson-White Syndrome (WPW), Premature Ventricular Contraction (PVC), Ventricular Bigeminy (Bigeminy), Ventricular Trigeminy (Trigeminy), Ventricular Tachycardia (VT), Idioventricular Rhythm (IVR), Ventricular Flutter (VFL), Fusion Beats (Fusion), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Sudden Bundle Branch Block (SDHB), and Premature Rhythm (PR).

3. Methodology

In this study, ECG signals of 17 different arrhythmia signals were filtered with different methods. In order to evaluate the performance of the IIR filter (Butterworth), EMD, and VMD methods, the output of each method is compared with the original ECG signal. All processes were carried out using the MATLAB program. Statistical metrics such as correlation coefficient, Mean Square Error (MSE), and Signal-to-Noise Ratio (SNR) were used as comparison metrics. Thus, the extent to which each filtering technique preserves the original signal, its robustness to distortion, and its reconstruction performance are quantitatively evaluated. This approach comparatively demonstrates the effectiveness of methods that aim to remove noise with minimal interference to the structural properties of the signal. The three main methods used in this study, Butterworth filtering, EMD, and VMD, are signal processing approaches based on different mathematical foundations:

Butterworth filtering is a classical digital filtering technique that passes components in a specific frequency band and suppresses the rest. The transition region is smooth and can be designed to be as close to an ideal frequency response as possible. $H(w) = \frac{1}{\sqrt{1+(\frac{w}{w_c})^{2n}}}$ is defined by the formula where w_c is the cutoff frequency and *n* is the filter order. The advantage of IIR filters over FIR filters is that successful results can be achieved by using a lower filter degree.

EMD was proposed by Huang in 1998 and is designed to decompose nonlinear and non-stationary signals [14]. EMD separates a signal into oscillatory components called *Intrinsic Mode Functions (IMFs)*, which reveal the signal's frequency content over time. Each IMF has the same length as the original signal and must satisfy two main conditions: (1) the number of extrema and zero crossings must be approximately equal, and (2) the average of the upper and lower envelopes should be close to zero (Eq. (1)). The EMD algorithm identifies local maxima and minima to construct envelopes, calculates their mean, and subtracts this from the signal to obtain a detail signal (Eq. (2)). This process is repeated until an IMF is obtained, and the entire process is repeated on the residual signal until all IMFs are extracted. This method decomposes the signal based on its structure without using a predefined basis.

$$m(t) = (emax(t) + emin(t)) / 2 \tag{1}$$

$$d(t) = X(t) – m(t) \tag{2}$$

VMD is a variational approach that aims to decompose the signal into modes with specific center frequencies. Each mode is obtained in a narrow-band and purpose-optimized manner. VMD operates in a more stable and mathematically controlled framework than EMD. VMD has a mathematical definition as seen in Eq. (3). This formulation splits a given signal u(t) into K modes, $u_k(t)$, each with a specific center frequency w_k [15].

$$\min_{\{u_k\},\{w_k\}} \left\{ \left\| \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{i}{\pi t} \right) * u_k(t) \right] e^{-jw_k t} \right\|_2^2 \right\} \tag{3}$$

Firstly, the amplitude of the ECG signals was normalized between 0-1 for a more accurate analysis of the metrics to be calculated for comparison. Then, by trial and error, the cutoff frequency of the

IIR filter was determined as [1-60 Hz], and the 4th-order bandpass Butterworth filter was applied to all signals. In the EMD and VMD methods, as seen in Figures 2 and 3, it was first decomposed into a maximum of 9 IMFs. According to the frequency change in EMD, it was decided that decomposition into five would be sufficient, and 5 IMFs were obtained with both methods. Noise elimination was achieved by iteratively recombining the IMFs, and in order to remove the noise with high frequency components that affect the ECG the most, the noise-free signal was obtained by collecting IMFs 2-5 without taking the first IMF signal. Figure 1 and Figure 2 show an example of the nine modes based on the EMD and VMD of the ECG signals for NSR, respectively.

To evaluate and compare the performance of the Butterworth, EMD, and VMD filtering methods, several quantitative metrics are used: Pearson correlation coefficient, MSE, and SNR. These metrics measure how closely the filtered signal resembles the original unfiltered signal and provide a comprehensive assessment of how effectively each method preserves signal integrity while removing noise. Correlation Coefficient (r) measures the linear relationship between the original and filtered signals. A high r value (close to 1) will indicate that the signals are similar to each other. MSE calculates the average difference between raw and filtered signals. Lower values imply higher performance. SNR measures the difference between the original and filtered signal power. It is calculated as the logarithmic ratio of the power of the raw signal to the power of the noise. A higher SNR suggests better noise reduction.

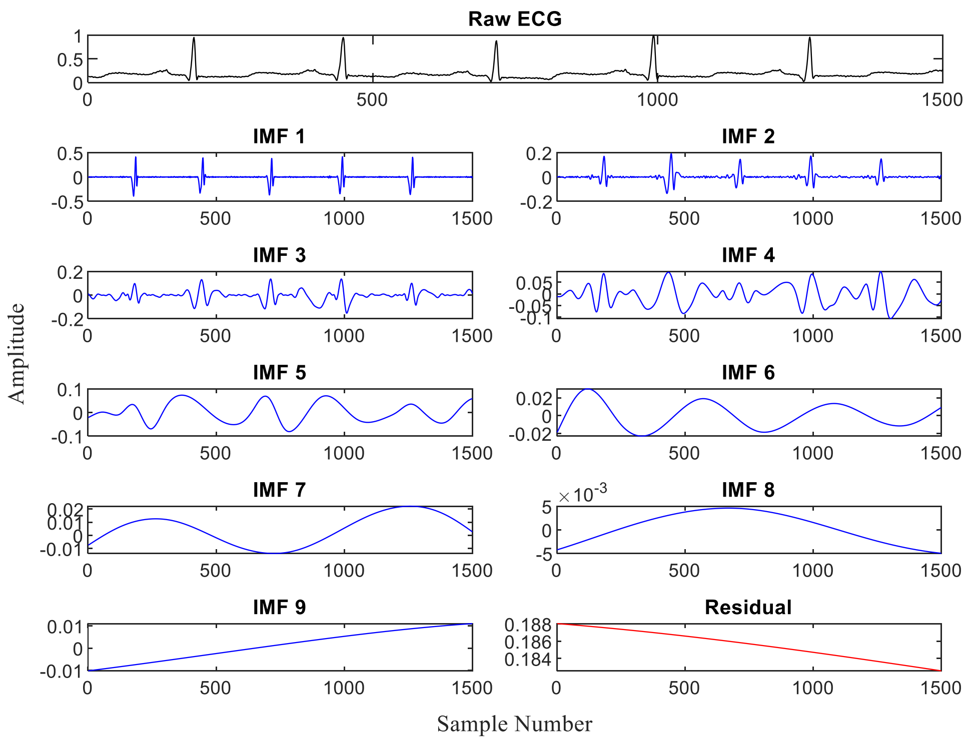

Figure 1. Illustration of nine EMD modes, raw ECG, and residual signals.

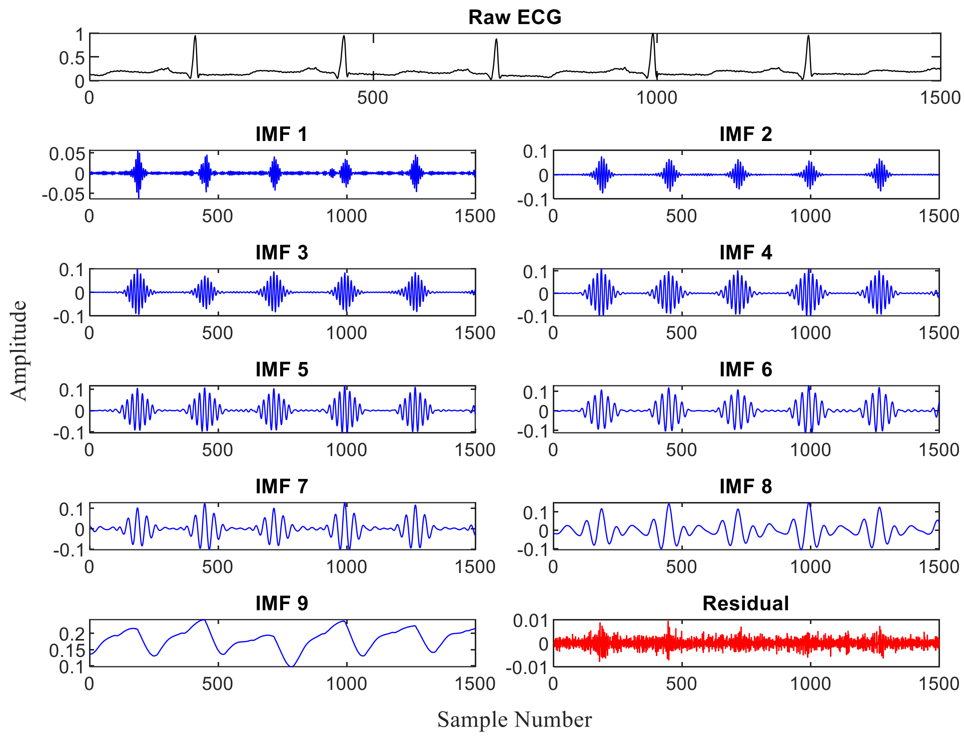

Figure 2. Illustration of nine VMD modes, raw ECG, and residual signals.

4. Results and Discussion

The results were compared with the mean and standard deviation of the calculated metrics. When Table 2 is examined, the averages of correlation, MSE, and SNR values obtained on 17 different ECG rhythm classes using IIR filtering, EMD, and VMD methods are compared. In general, the VMD method shows superior performance in all metrics. When the correlation values are examined, VMD provides the filtered output closest to the raw signal by providing values above 0.98 on average. In addition, the MSE values of VMD are extremely low (usually below 0.001), which shows that the error after filtering is very low. VMD also stands out clearly in terms of SNR, providing values above 20 dB for most classes, which shows the high signal quality. On the other hand, the IIR filtering method produced higher MSE and lower SNR values compared to VMD. However, it generally provides better correlation and SNR results than EMD. Although the EMD method performed similarly to IIR in some classes (e.g., VT, IVR), especially in correlation, it generally performed poorly with higher MSE and lower SNR values. These results reveal that VMD is the most effective method in ECG signal filtering in terms of both accuracy and signal-noise separation. While IIR gives reasonable results due to its classical structure, EMD is less effective in noise separation. In this context, the VMD method should be preferred in clinical applications that require high accuracy, low error, and high signal quality. However, the selection should consider processing time and computational cost factors. The filtering result for an ECG signal of a normal sinus rhythm is given in Figure 3. When the filtering process is examined visually, it is seen that the Butterworth filter and the VMD method provide good filtering, while the EMD is less successful.

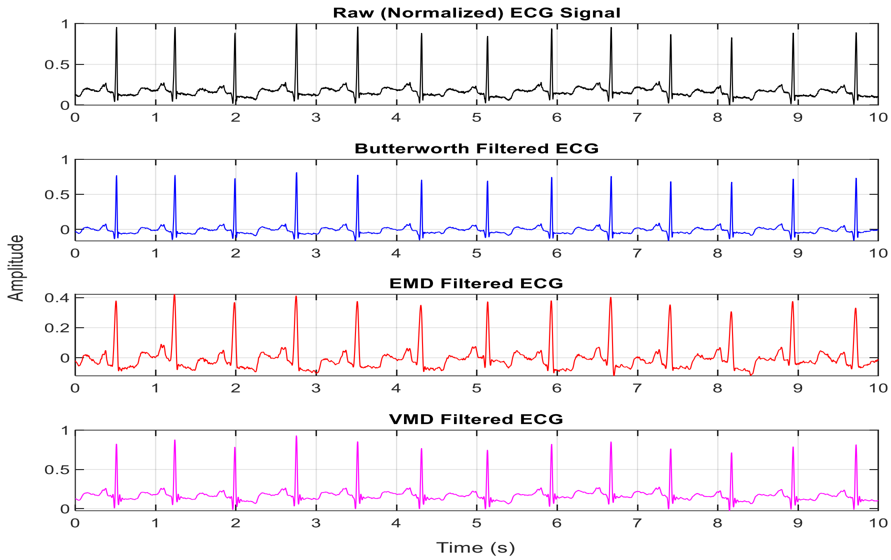

Figure 3. ECG signal filtering comparison for NSR

Table 2. Average metric values for each class

	IIR Filter			*EMD*			*VMD*		
Class	Correlation	MSE	SNR	Correlation	MSE	SNR	Correlation	MSE	SNR
NSR	0.9183	0.0977	1.1458	0.8342	0.1029	0.7024	0.9798	0.0006	22.4602
VT	0.8904	0.1502	0.6082	0.9170	0.1507	0.5345	0.9919	0.0004	26.4974
IVR	0.9196	0.0959	0.9936	0.9278	0.1136	0.2580	0.9990	0.0001	33.2762
VFL	0.9033	0.2027	0.5423	0.8954	0.2092	0.4075	0.9972	0.0001	34.3449
Fusion	0.9278	0.1118	0.7305	0.8469	0.1166	0.4598	0.9768	0.0008	22.0953
LBBBB	0.9350	0.1085	0.9784	0.8971	0.1137	0.6445	0.9943	0.0002	29.1830
RBBBB	0.9267	0.1242	0.7324	0.8728	0.1274	0.5178	0.9866	0.0005	24.2966
SDHB	0.9159	0.0252	1.1113	0.8178	0.0280	0.6474	0.9723	0.0005	18.2895
PR	0.9606	0.2758	0.3839	0.9311	0.3040	-0.0559	0.9970	0.0002	33.3167
APB	0.8990	0.1107	0.6205	0.7638	0.1162	0.3182	0.9705	0.0007	22.4959
AFL	0.7988	0.0930	0.8802	0.7921	0.0986	0.5149	0.9836	0.0006	22.9148

Table 3 shows the average correlation, MSE, and SNR values on all ECG signals of the methods used in the study. The VMD method has the highest correlation value (0.9838) and the lowest MSE value (0.0005). This shows that the filtered signal is closest to the raw signal with VMD. It also has a very high SNR value (25.2979), indicating that the signal is successfully cleaned against noise. The IIR filter performs best after VMD. It has a high correlation value (0.9190) but is weaker than VMD regarding MSE and SNR. Nevertheless, it performed better than EMD. The EMD method shows the poorest performance with the lowest correlation (0.8666) and the highest MSE (0.1321). It also has a very low SNR value (0.4664), indicating poor noise removal performance.

Table 3. Average metric values for all ECG signals

	Correlation	MSE	SNR
IIR Filter	0.919031	0.125452	0.806111
EMD	0.866574	0.132123	0.466387
VMD	0.983827	0.000487	25.29788

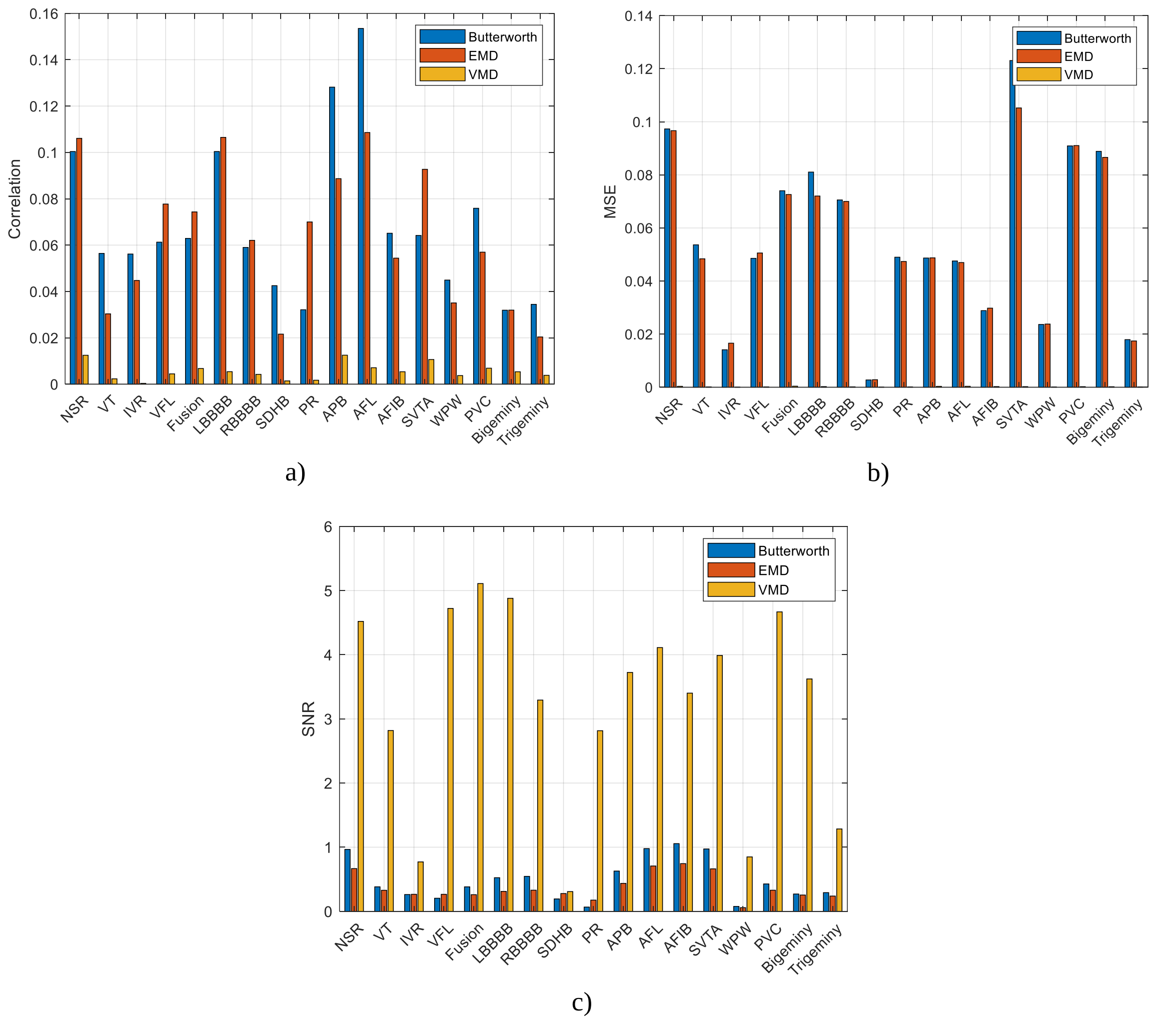

Figure 4. Standard deviations of metrics: a) correlation, b) MSE, c) SNR for each ECG class

Figure 4 shows the standard deviation values of three signal processing methods (Butterworth filter, EMD, and VMD) applied for different ECG rhythm classes. According to the results, the Butterworth filter generally has higher standard deviations, which reveals that the method exhibits inconsistent performance between different classes. Although the EMD method provides more stable results in some classes, it generally shows moderate variability. On the other hand, the VMD method stands out with its low standard deviation values in terms of both correlation coefficient, MSE, and SNR. This shows that VMD provides more consistent and reliable performance regardless of the signal class and, therefore, is a method that can be preferred in practical applications.

When this study was compared with other studies in the literature, Bentaleb et al. [16] achieved significant success in the denoising and classifying ECG signals with the hybrid filtering and multi-criteria Bayesian optimization approach. They increased the signal quality by combining EEMD, Chebyshev II, Butterworth, Daubechies Wavelet, and Savitzky–Golay filters and achieved up to 98.03% accuracy in classifying arrhythmia and myocardial infarction with deep learning. They emphasized the importance of filtering the ECG signal, argued that the hybrid method was more successful than a single filtering method, and used 5 different methods simultaneously. They measured filtering success with correlation and MSE. As a result, MSE was obtained as 0.063 and the correlation value as 0.964 with the hybrid method, but when the EMD method was removed, MSE increased, and the correlation value decreased. The cut-off frequency of the Butterworth filter was determined as [0.961-60 Hz] [16]. The difference of this study from the study conducted by Bentaleb et al. [16] because the correlation value was 0.984 and the MSE was 0.0005 with the VMD method. Zhao et al. [17] proposed an ECG compression method based on Ensemble EMD and DWT, aiming to reduce the mode mixing problem of the signal and improve compression efficiency. They used the MIT-BIH arrhythmia dataset and obtained an average SNR of 18.27 and Root MSE of 3.17 percent due to filtering [17]. In this study, although the arrhythmia class is higher, the SNR value is higher. Ma et al. [18] proposed a new particle filtering algorithm using six-axis sensor data to eliminate motion artifacts in ECG signals recorded with wearable devices during sports. ECG modeling was performed using VMD and Laguerre estimation. Particle weights were updated adaptively with the γ parameter obtained from the sensor data, and thus, a high amount of noise was successfully filtered. In the study by Menaceur et al. [19], three different filtering methods for ECG signals, namely linear, nonlinear, and adaptive, were comparatively examined. The results revealed that the adaptive median filter, especially with a kernel parameter of 5, provided more successful noise removal than other methods by adapting to the dynamic ECG signal structure with 17.845257 SNR and 0.001587 MSE values. Malleswari et al. [20] presented a multi-level denoising method based on EMD and wavelet transform to eliminate various noises (AWGN, Baseline Wander, PLI) in ECG signals using MIT-BIH arrhythmia database. They achieved better results than existing studies in performance criteria such as RMSE, SNR, cross-correlation with the thresholding technique applied using 'Sym8' wavelet family. The main difference between these three studies and the present work is that the proposed method achieves a higher SNR value and a correlation value very close to 1 by using the VMD technique. Zhang et al. [21] proposed a denoising method based on VMD combined with Recursive Least Squares (RLS) adaptive filtering for ECG signals. They reported that their method eliminates various types of noise, including Gaussian white noise, baseband drift, electrode motion, electromyographic interference, and electrical interference by decomposing the noisy signal using VMD and adaptively filtering each intrinsic mode function (IMF) with RLS. They performed separate analyses for different noise types and compared methods using SNR and Root MSE. The VMD-RLS filtering method outperformed the others, achieving SNR values between 18 and 26.

In comparison to previous studies, the results from this study highlight the superior performance of the VMD method in ECG signal denoising and classification. While studies such as those by Bentaleb et al. [16] and Zhao et al. [17]report promising results with hybrid filtering techniques and ensemble methods, the VMD method achieves even higher correlation (0.984) and significantly lower MSE (0.0005), indicating its superior ability to preserve the original signal quality. The SNR values obtained in this study (25.2979) are also among the highest reported, surpassing those of previous methods like the VMD-RLS filtering approach by Zhang et al. [21]. Overall, the VMD technique offers more consistent and reliable performance across different ECG rhythm classes compared to other methods evaluated in the literature, making it a strong candidate for practical applications in ECG signal processing.

Conclusion

Accurate analysis and diagnosis of ECG signals heavily rely on efficient noise removal techniques. In this study, a range of filtering strategies were explored, spanning from traditional digital filters to advanced decomposition methods (EMD, VMD). The ongoing studies into the filtering of ECG signals underscore the importance of this topic and indicate that no universally proven method has yet been established. The contribution of this study to the literature is its comparison of classical filtering methods with EMD and VMD decomposition techniques across a wide range of arrhythmia classes (17 classes). The goal is to identify a common filtering approach that can be effectively applied to all types of arrhythmia signals. In conclusion, the VMD method stands out for its superior average performance and lower variance, enhancing its suitability for clinical applications. In future studies, it is planned to develop hybrid filtering frameworks that combine multiple methods to achieve more robust results and to compare classification performance based on feature extraction.

References

1. Kossmann, C. E., 1953. The normal electrocardiogram. Circulation, 8(6): 920–936.
2. Gopinathannair, R., Etheridge, S. P., Marchlinski, F. E., Spinale, F. G., et al., 2015. Arrhythmia-induced cardiomyopathies: mechanisms, recognition, and management. Journal of the American College of Cardiology, 66(15): 1714–1728.
3. Wan, X., Liu, Y., Mei, X., Ye, J., et al., 2024. A novel atrial fibrillation automatic detection algorithm based on ensemble learning and multi-feature discrimination. Medical & Biological Engineering & Computing, 62(6): 1809–1820.
4. Ojha, M. K., Wadhwani, S., Wadhwani, A. K., Shukla, A., 2022. Automatic detection of arrhythmias from an ECG signal using an auto-encoder and SVM classifier. Physical and engineering sciences in medicine, 45(2): 665–674.
5. Kumar, K. S., Yazdanpanah, B., Kumar, P. R., 2015. Removal of noise from electrocardiogram using digital FIR and IIR filters with various methods. *2015 International conference on communications and signal processing (ICCSP)* (pp. 157–162). IEEE.
6. Wang, K.-C., Liu, K.-C., Peng, S.-Y., Tsao, Y., 2023. Ecg artifact removal from single-channel surface emg using fully convolutional networks. *ICASSP 2023-2023 IEEE*

International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 1–5). IEEE.

7. Noskova, E., Tumakov, D., 2024. Analysis of wavelet transform application for filtering real ecg signals from high-frequency noise. *2024 26th International Conference on Digital Signal Processing and its Applications (DSPA)* (pp. 1–5). IEEE.
8. Singh, O., Sunkaria, R. K., 2017. ECG signal denoising via empirical wavelet transform. Australasian physical & engineering sciences in medicine, 40: 219–229.
9. Das, M., Sahana, B. C., 2025. A Deep-learning-based Auto Encoder-Decoder Model for Denoising Electrocardiogram Signals. IETE Journal of Research, 71(1): 326–340.
10. Issa, M. F., Yousry, A., Tuboly, G., Wang, Z., et al., 2025. Enhancing single-lead electrocardiogram arrhythmia detection with empirical mode decomposition. Neural Computing and Applications, 1–23.
11. Lahmiri, S., 2014. Comparative study of ECG signal denoising by wavelet thresholding in empirical and variational mode decomposition domains. Healthcare technology letters, 1(3): 104–109.
12. Plawiak, P., 2017. ECG signals (1000 fragments). Mendeley Data, v3.
13. Altıntop, Ç. G., 2025. Kalp Ritim Bozukluklarının Çok Sınıflı Sınıflandırılmasında ReliefF Yöntemi ve Makine Öğrenimi Tabanlı Yaklaşım TT - The ReliefF Method and Machine Learning-Based Approach in the Multi-Class Classification of Cardiac Arrhythmias. Black Sea Journal of Engineering and Science, 8(3): 3–4. (https://doi.org/10.34248/bsengineering.1566475)
14. Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., et al., 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London. Series A: mathematical, physical and engineering sciences, 454(1971): 903–995.
15. Dragomiretskiy, K., Zosso, D., 2013. Variational mode decomposition. IEEE transactions on signal processing, 62(3): 531–544.
16. Bentaleb, D., Khatar, Z., 2025. Multi-criteria Bayesian optimization of Empirical Mode Decomposition and hybrid filters fusion for enhanced ECG signal denoising and classification: Cardiac arrhythmia and myocardial infarction cases. Computers in Biology and Medicine, 184: 109462.
17. Zhao, S., Gui, X., Zhang, J., Feng, H., et al., 2025. An improved ECG data compression scheme based on ensemble empirical mode decomposition. Biomedical Signal Processing and Control, 101: 107134.
18. Ma, M., Du, M., Feng, Q., Xiahou, S., 2024. A new particle filter algorithm filtering motion artifact noise for clean electrocardiogram signals in wearable health monitoring system. Review of Scientific Instruments, 95(1).
19. Menaceur, N. E., Kouah, S., Derdour, M., 2024. Adaptive filtering strategies for ecg signal enhancement: A comparative study. *2024 6th International Conference on Pattern Analysis and Intelligent Systems (PAIS)* (pp. 1–6). IEEE.
20. Malleswari, P. N., Bindu, C. H., Prasad, K. S., 2024. Denoising methods for removal of Baseline Wander, AWGN and power line interface noises in ECG signal: a comparative analysis. Australian Journal of Electrical and Electronics Engineering, 1–11.
21. Zhang, C., Chen, W., Chen, H., 2025. Denoising for ECG signals based on VMD and RLS. Journal of Measurements in Engineering, 13(1): 185–204.