Wavelet-Based ECG Denoising: A Comparative Study of Empirical and Stationary Wavelet Transforms

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**Abstract.** Electrocardiogram (ECG) is the critical tool in measuring the cardiac condition of patients. However, during the step of signal acquisition, the ECG will often interrupt by some of the noise, and the noise may obscure some of the critical details in the signal. Therefore, in order to eliminate and reduce the noise of the signal, we have implemented two wavelet-based noise reduction techniques, Stationary Wavelet Transform (SWT) and Empirical Wavelet Transform (EWT) in this study. On the other hand, we do also introduce and add two types of noise (Baseline Wander (BW) and Electromyogram (EMG) into 48 recordings of the ECG signal from MIT-BIT Arrhythmia Dataset individually for the purpose of accessing the effectiveness of these noise reduction methods on reducing the noise on the signal. Besides, the evaluation metrics that have been used in this study to evaluate the performance of the noise reduction approaches are Signal-to-Noise Ratio (SNR), Root Mean Squared Error (RMSE), and Percent Root Mean Square Difference (PRD). Based on our experiment, SWT has outperformed compared to EWT in reducing both BW and EMG, whereby SWT has scored the higher average SNR, and the lower average RMSE, and average PRD.

# iNTRODUCTION

Electrocardiogram (ECG) is a non-stationary, non-linear, quasiperiodic time series data extensively utilized in measuring and evaluating the electrical and muscular heart activities [1]. However, noisy and artifact ECG signals are the common impediments during acquisition. The main factors that cause the occurrence of the noise to the signal are inadequate electrode-skin contact, improper electrode placement, muscular activity, respiration, nearby electrical equipment, or even the internal circuitry of the ECG machine itself [2].

The most typical ECG noise is Baseline Wander (BW), Power Line Interference (PLI), Electromyogram (EMG), and Electrode Motion Artifacts (EMA). BW is a low frequency artifact usually generated due to patient respiration or motion which conceals important signal parts in the low frequency range [3]. The muscular and ocular activity presents EMG noise [1], PLI is due to electromagnetic interference of the environment, usually at 50 or 60 Hz [3]. EMA, in its turn, happens as a result of physical movement of electrodes and may resemble real cardiac activity, making the mistake of misdiagnosis more possible [3].

The occurrence of these noises on the ECG will obscure the important features of the signal and it will indirectly affect the readability of the ECG signal. As a result, clinical diagnosis made based on the ECG readings may be inaccurate. Hence, efficient denoising is necessary to guarantee high fidelity to the interpretation of ECG signals and improve the precision of the diagnosis.

Even though the conventional filtering techniques including linear filters, notch filters, and bandpass filters have been applied to deal with the ECG noise, they are sometimes not sufficient to make the preservation, but diagnostically important signal details. To overcome this shortcoming, there has been growing popularity in the use of wavelet-based denoising methods because they offer a framework to deal with the non-stationary and multi-resolution signal that ECG representations are. Such methods as Empirical Mode Decomposition (EMD), Empirical Wavelet Transform (EWT), Discrete Wavelet Transform (DWT), and Stationary Wavelet Transform (SWT) have demonstrated potential in other research [4].

Although wavelet-based denoising methods are increasingly used, but it is still not understood which of the many available methods provide an optimal trade-off between noise reduction and preservation of the signal (especially for the most diagnostically disruptive types of noise such as BW and EMG). Such absence of comparative study serves as a challenge to practitioners who would want to find out the best denoising strategies to use.

Thus, the purpose of this work is to assess and compare two methods of wavelet-based denoising, EWT and SWT, in the elimination of BW and EMG noise. The goal of us is to verify and determine which noise reduction methods are better in eliminating the noise of signal while also preserving the most detail of original signal detail.

This paper has been divided into 5 sections. Section 1 will provide the overview of this study; Section 2 will provide the overview of our study based on past research; Section 3 will discuss the methodology used in this work; Section 4 will present and discuss the experimental results based on our work; Section 5 will conclude and make the wrap up for our paper.

# LITERATURE REVIEW

Techniques based on wavelets have been found to be useful in denoising ECG signal because they provide a multi-resolution decomposition of signals, and they are able to deal with non-stationary properties. EWT is one of them and has been given significant attention. In contrast to conventional wavelets, EWT performs the adaptive construction of wavelet filters in the Fourier domain, thus it can target the signal components more selectively [5]. Azzouz et al.[6] demonstrated that EWT outperforms the Signal-to-Noise Ratio (SNR) considerably and is a robust noise suppressing technique thus it has potential in ECG preprocessing.

In an attempt to further improve performance of denoising, some of the researchers have investigated the hybrid methods. For instance, Boda et al.[7] have used EWT along with Empirical Mode Decomposition (EMD) to end up with an EMD-EWT method that significantly removed 50 Hz PLI and maintained important ECG characteristics. Their findings expressed the advantage of the method compared to some of the traditional methods in improving SNR as well as reducing diagnostic distortion [7].

Conversely, SWT is slightly different to other wavelet approaches in that it does not employ down-sampling in the decomposition procedure [8]. This translation-invariant property allows SWT to retain signal detail more effectively during denoising [9]. Kumar et al. [2] found that SWT performs better compared to the other methods, including DWT, EMD, and Fourier Decomposition Method (FDM) in important performance measurements, including SNR, PRD, and RMSE. These results highlight the fact that SWT is efficient in maintaining important ECG features, especially the QRS complex, and at the same time, it noticeably diminishes noise.

Besides, Dwivedi et al.[10] developed a hybrid denoising strategy by combining Ensemble Empirical Mode Decomposition (EEMD) with SWT. Their method also reduced high-frequency noise by using the refinement of Intrinsic Mode Functions (IMFs), which showed a great sense of performance in preserving the ECG signal. The combination was particularly useful in eliminating PLI and it had achieved the best SNR improvements compared to the other techniques that were tested [10].

Both EWT and SWT have demonstrated significant potential, but the literature tends to concentrate on the hybrid variants of those or test them in vacuity with various data sets or evaluation measures. The effective comparison between EWT and SWT is still quite restricted and narrow, especially on the typical kinds of noise such as BW and EMG. This gap does not help the practitioners to make an informed choice regarding which method is better to use in a general ECG denoising applications.

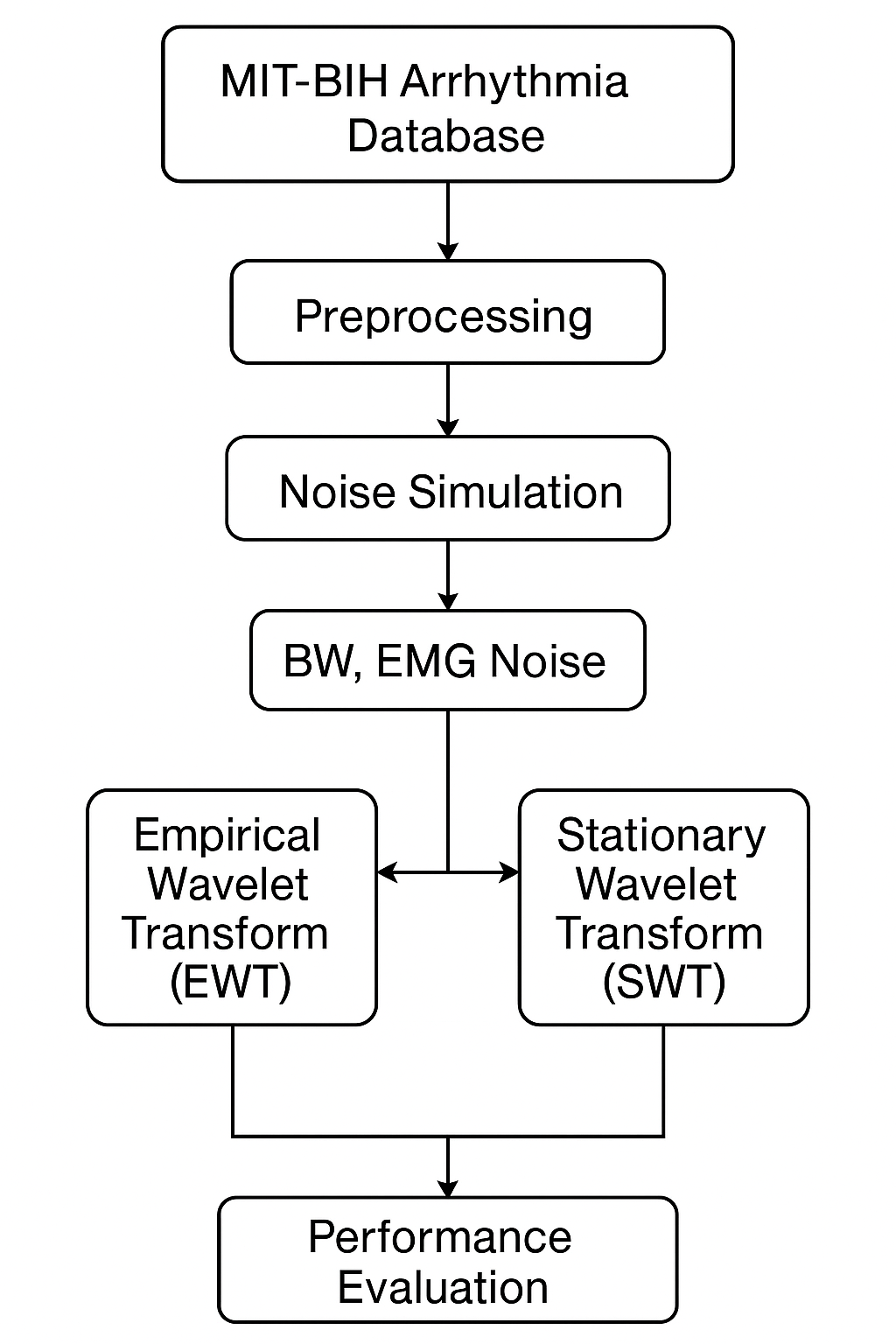
Therefore, this research will seal this gap by performing a comparative analysis between EWT and SWT, analyzing their effectiveness in the elimination of BW and EMG noises. The purpose is to find out which one produces greater signal fidelity and facilitates efficient cardiac diagnosis, thus providing feasible knowledge to ECG signal processing.

# METHODOLODY

In order to determine the suitability of EWT and SWT in denoising ECG signals, the study takes a controlled experimental design, which uses publicly available ECG datasets. This study seeks to establish the most effective method by emulating real-life noisy environment and by subjecting the two methods to the same environment, establish which algorithm is better at retaining vital ECG characteristics, and at the same time reduce noise interference. Figure 1 shows the general flowchart and the description of the process is presented in the subsections below.

## Dataset Selection and Preprocessing

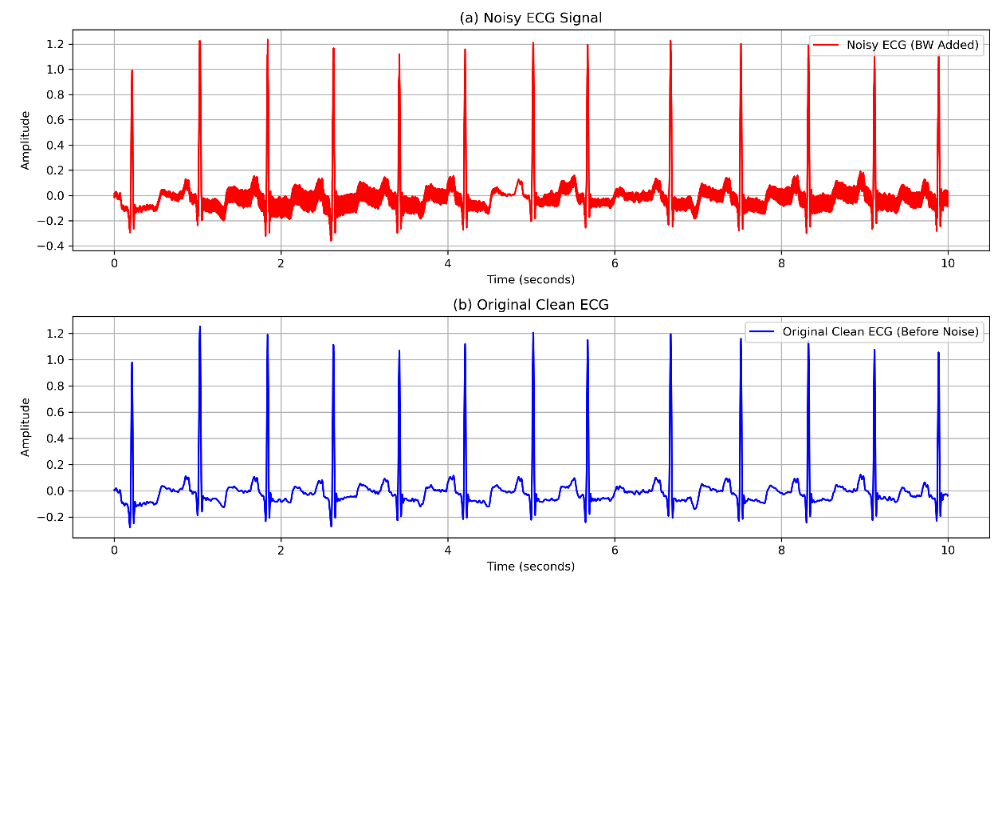
The primary dataset that used in this study is the MIT-BIH Arrhythmia Database, chosen for its comprehensive coverage of diverse ECG signal patterns. The dataset comprises 48 half-hour ECG recordings collected from a broad range of cardiac conditions [11]. The first 10 seconds of all 48 recordings were extracted for this experiment and used as the baseline clean ECG signals. The main reason for selecting only the first 10 seconds of the recording is because this duration is sufficient for capturing the key cardiac pattern of the signal meanwhile reduce computation cost on processing the whole recordings of the signal. Prior to any noise addition, each ECG signal underwent basic preprocessing using bandpass filtering to remove any inherent noise and ensure a clean reference signal for testing.



**FIGURE 1.** The overall flowchart of the experiment

## Noise Simulation

To closely replicate realistic clinical scenarios, two types of common ECG noise were introduced: BW and EMG. These noise samples were retrieved from the MIT-BIH Noise Stress Test Database. Each noise type was individually added to the clean ECG signals at a SNR of 10 dB, simulating the level of interference typically encountered during actual signal acquisition due to respiration, muscular movement, or poor electrode contact. This process enabled us to rigorously test the denoising capability of both EWT and SWT on independently noisy signals. Figure 2 and 3 visualize the noisy ECG signal compared to the cleaned ECG signal.



**FIGURE 2.** (a) Noise ECG signal (Clean ECG signal + BW) (b) Clean ECG signal

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**FIGURE 3.** (a) Noise ECG signal (Clean ECG signal + EMG) (b) Clean ECG signal

## ECG Denoising Techniques

Two ECG denoising methods, EWT and SWT, were implemented and compared in this study. EWT is an adaptive technique designed specifically for handling non-stationary signals like ECG. Unlike predefined wavelet families, EWT constructs wavelet filters directly from the signal’s Fourier spectrum, allowing the transform to adapt to the signal’s content[7]. Besides, EWT is an adaptability method that enables signal to precisely isolate frequency bands corresponding to different signal components and noise enabling it to be used as an effective tool for ECG denoising. EWT decomposes the signal into multiple frequency bands and hence is able to perform targeted noise reduction without losing the important morphological properties of the ECG [7]. In this study, EWT will begin by creating the adaptive wavelet functions that are suitable for the ECG signal by itself. After done with create the adaptive wavelet function, EWT will decompose the signal into three frequency bands, which are low, mid, and high frequency elements. After that, the soft thresholding will be applied to mid and high frequency elements only because the low frequency elements are more often contain most of the key features of the signal. Therefore, applying the thresholding to the mid and high frequency elements can effectively eliminate the noise of the signal while also preserving the key feature of the signal. Lastly, after doing the thresholding, all of the decomposed signals will be reconstructed and become the clean and denoised signal.

SWT, also known as the translation-invariant wavelet transform, improves upon DWT by avoiding down-sampling during decomposition. This ensures better preservation of the signal’s temporal structure. Comparing to DWT, SWT does not suffer down-sampling and up-sampling and hence is better preserved the alignment of signal features. Especially for ECG signals, this property is very important since preserving the morphology of P wave, QRS complex and T wave determines the diagnostic value. SWT is particularly well suited for working with noise from a low or high frequency range such as BW, EMG noise, and PLI [9]. SWT will begin by decomposing the signal into multiple levels, which are four levels, and each level will consist of approximation coefficients (cA) and detail coefficients (cD). For wavelet function selection of SWT in this study, unlike EWT will create the wavelet function by itself, SWT may need to define the wavelet function by ourselves, and the wavelet function used in this study is sym4. SWT will only perform up-sampling on the wavelet function to align the length of each coefficient at each decomposition level. Both coefficients will be applied to soft thresholding to reduce the noise on the coefficients. However, the thresholding value on both cA and cD will be different, whereby cA will be applied with more lower thresholding value, and cD will be applied with more higher thresholding value. After the thresholding is done, both coefficients will be reconstructed and become a cleaned and denoised signal using Inverse Stationary Wavelet Transform (ISWT). Figure 4 and 5 visualize the denoised signal after removing BW and EMG using SWT and EWT, respectively.

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| (a) | (b) |

**FIGURE 4.** (a) Denoised ECG signal using SWT (b) Denoised ECG signal using EWT

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| (a) | (b) |

**FIGURE 5.** (a) Denoised ECG signal using SWT (b) Denoised ECG signal using EWT

To quantitatively assess the denoising performance of both methods, SNR, RMSE, and PRD are used. SNR will measure overall signal clarity after denoising, RMSE will quantify the deviation between original and denoised signals, and PRD will evaluate the relative difference between original and denoised signals. In SNR, the power of desired signal is representing the energy of the actual ECG signal, and the power of noise is representing the energy of the noise or unwanted interference present in the signal. While for the PRD and RMSE, the is representing the sample of the original ECG signal, is representing the sample of the denoised ECG signal, and N is representing the total number of sample. These metrics are computed for each denoised output to compare how effectively each method reduces noise while preserving the integrity of the ECG waveform. The equations for these metrics are presented in Equations (1), (2) and (3).

1

2

3

# Result And DISCUSSION

The denoising effectiveness of EWT and SWT was assessed by three performance measures: SNR, RMSE, and PRD. Table 1 contains the results of each technique in two kinds of simulated noise, BW and EMG.

**TABLE 1.** The denoising performance of EWT and SWT

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Denoising Technique** | **Noise** | **SNR (dB)** | **RMSE** | **PRD (%)** |
| EWT | BW | 12.51 | 0.0752 | 23.54 |
| EMG | 11.87 | 0.0817 | 25.60 |
| SWT | BW | 17.24 | 0.0432 | 14.19 |
| EMG | 14.93 | 0.0589 | 18.19 |

SNR is measuring the overall signal clarity after denoising and the effectiveness of a denoising algorithm. A higher SNR indicates better noise suppression while preserving the useful part of the ECG signal. For BW, SWT achieved the highest SNR of 17.24 dB, outperforming EWT, which recorded 12.51 dB. For EMG, SWT again outperformed EWT with an SNR of 14.93 dB compared to 11.87 dB. This finding demonstrates that SWT is more effective in enhancing signal clarity and suppressing noise across both types of disturbance.

RMSE quantifies the average error magnitude between the original and denoised signal, where lower RMSE values indicate better denoising performance. Table 1 shows that SWT achieved a significantly lower RMSE in terms of BW of 0.0432, compared to 0.0752 for EWT. For EMG, SWT again showed superior performance with an RMSE of 0.0589, while EWT recorded 0.0.817. The results indicate that SWT introduces fewer errors in the reconstruction of the ECG signal after denoising.

PRD evaluates the distortion between the original clean and the denoised signal. A lower PRD suggests better preservation of ECG features after denoising. For BW, SWT achieved a PRD of 14.19%, which is considerably lower compared to EWT with 23.54% of PRD. For EMG, SWT showed a PRD of 18.19%, while EWT scored 25.60%. Again, SWT demonstrated a better ability to preserve the diagnostic features of the ECG signal.

Across all performance metrics, SWT consistently outperformed EWT for both types of noise. SWT not only improved noise suppression but also preserved the integrity of ECG signal features more effectively. These findings suggest that SWT is a more reliable and accurate denoise technique for ECG preprocessing in clinical and research applications.

# Conclusion

This study evaluated the performance of two wavelet-based denoising techniques, EWT and SWT, in reducing BW and EMG from ECG signals. Using 48 recordings from the MIT-BIH Arrhythmia Database with simulated noise from the MIT-BIH Noise Stress Test Database, we assessed denoising effectiveness through SNR, RMSE, and PRD. The experimental results demonstrate that SWT has consistently outperformed EWT, achieving higher average SNR and lower average RMSE and average PRD values, thus providing clearer, more reliable ECG signals. While EWT showed some promise, its performance was less consistent across different signal types. Overall, SWT proved to be a more effective and robust approach for ECG denoising, making it a suitable candidate for clinical ECG preprocessing usage.

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# References

1. S. Chatterjee, R.S. Thakur, R.N. Yadav, L. Gupta, and D.K. Raghuvanshi, “Review of noise removal techniques in ECG signals,” IET Signal Process. **14**(9), 569–590 (2020).
2. A. Kumar, H. Tomar, V.K. Mehla, R. Komaragiri, and M. Kumar, “Stationary wavelet transform based ECG signal denoising method,” ISA Transactions **114**, 251–262 (2021).
3. R. Kher, “Signal Processing Techniques for Removing Noise from ECG Signals,” Journal of Biomedical Engineering and Research, (2019).
4. B.K. Pradhan, B.C. Neelappu, J. Sivaraman, D. Kim, and K. Pal, “A Review on the Applications of Time‐Frequency Methods in ECG Analysis,” Journal of Healthcare Engineering **2023**(1), 3145483 (2023).
5. I. Manea, and D. Taralunga, “Fetal ECG Extraction from Abdominal Signals Using Empirical Wavelet Transform,” in *2022 E-Health and Bioengineering Conference (EHB)*, (IEEE, Iasi, Romania, 2022), pp. 1–4.
6. A. Azzouz, B. Bengherbia, P. Wira, N. Alaoui, A. Souahlia, M. Maazouz, and H. Hentabeli, “An efficient ECG signals denoising technique based on the combination of particle swarm optimisation and wavelet transform,” Heliyon **10**(5), e26171 (2024).
7. S. Boda, M. Mahadevappa, and P.K. Dutta, “A hybrid method for removal of power line interference and baseline wander in ECG signals using EMD and EWT,” Biomedical Signal Processing and Control **67**, 102466 (2021).
8. S.A. Malik, S.A. Parah, and G.M. Bhat, “Electrocardiogram (ECG) denoising method utilizing Empirical Mode Decomposition (EMD) with SWT and a Mean based filter,” in *2021 2nd International Conference on Intelligent Engineering and Management (ICIEM)*, (IEEE, London, United Kingdom, 2021), pp. 322–326.
9. P. Madan, V. Singh, D.P. Singh, M. Diwakar, and A. Kishor, “Denoising of ECG signals using weighted stationary wavelet total variation,” Biomedical Signal Processing and Control **73**, 103478 (2022).
10. A.K. Dwivedi, H. Ranjan, A. Menon, and P. Periasamy, “Noise Reduction in ECG Signal Using Combined Ensemble Empirical Mode Decomposition Method with Stationary Wavelet Transform,” Circuits Syst Signal Process **40**(2), 827–844 (2021).
11. A.J. Khalaf, and S.J. Mohammed, “Verification and comparison of MIT-BIH arrhythmia database based on number of beats,” IJECE **11**(6), 4950 (2021).