Atrial Fibrillation Denoise Using Wavelet Adaptive Filter

Nur Izzani Mat Rozi
Faculty of Engineering, National Defence University of Malaysia

Tan Jia Min
Faculty of Engineering, National Defence University of Malaysia

Fakroul Ridzuan Hashim
Faculty of Engineering, National Defence University of Malaysia

Shazreen Shaharuddin
Faculty of Medical & Defence Health, National Defence University of Malaysia

他

https://doi.org/10.5109/7323266

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 10, pp.219-224, 2024-10-17. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：

Atrial fibrillation denoise using wavelet adaptive filter

Nur Izzani Mat Rozi[1], Tan Jia Min[2], Fakroul Ridzuan Hashim[3], Shazreen Shaharuddin[4], Maizatullifah Miskan[5]
[1,2,3]Faculty of Engineering, National Defence University of Malaysia, Sg. Besi Camp, 57000 Kuala Lumpur, Malaysia
[4,5]Faculty of Medical & Defence Health, National Defence University of Malaysia, Sg. Besi Camp, 57000 Kuala Lumpur, Malaysia
Corresponding author email: izzani299@gmail.com

Abstract: *This study assesses the efficacy of a descrete wavelet transform (DWT) which combines with adaptive filters (Af) in reducing noise in electrocardiogram (ECG) signals. Noise can compromise the accuracy of ECG signals, which are crucial for diagnosing heart diseases. Typical types of noise in signal processing include powerline interference (PLI), motion artefacts (MA), baseline wander (BW), and electromyogram (EMG) interference. These noise types as either correlated or uncorrelated and removing noises from ECG signal is crucial for achieving precise diagnoses. The research proposes the use combinations of Af-WT-based filters for the filtering process. The performance of the Af-WT-based filter will be compared to tWT and Af filters, with the Af-WT filter demonstrating the acceptable signal-to-noise ratio (SNR) measurement, denoisng the PLI, MA, BW and EMG form ECG signal.*

Keywords: electrocardiogram; diagnosing; interference; filtering; construct

1. INTRODUCTION

Atrial fibrillation (AF) is defined by an irregular and often rapid cardiac rhythm. The medical term for this irregular cardiac rhythm is arrhythmia [1]. 26,535 of the 183,321 death certificates issued in 2019 had AF as the cause of death. Additionally, the incidence of AF cases rises with advancing age [2]. Factors other than advancing age, such as obesity, smoking, and hypertension, can cause AF. The enhanced prediction algorithms have the potential to improve AF treatment and decrease AF patient incidence. Early treatment initiation can improve the accuracy of predicting the onset of AF, potentially saving lives. Although AF can manifest as symptoms such as tachycardia, dyspnea, and vertigo, many individuals may disregard these signs [2].

Developing a novel ECG analysis system is of utmost importance in order to collect initial data for the early identification of AF. The analysis includes two processor units: one for decomposing the ECG signal and another for filtering it. Due to the presence of excessive noise in the ECG, various noise cancellation techniques were employed to eliminate each specific disturbance from the ECG signal. However, most issues in ECG signal processing arise from noise that contaminates the ECG signal. The ECG signal contains four main types of noise: BW [3], PLI [4], EMG [5], and MA [6]. The standard digital filter allows for the removal of uncorrelated disturbances such as BW, PLI, and EMG. However, noises such as MA generated due to skeletal muscle activity are challenging to remove since their spectrum totally overlaps with that of the ECG signal. Employing an unsuitable filter may compromise the ECG signal's information and reduce noise. In terms of the outcomes, there is a possibility of encountering erroneous results, which might manifest as either false positives or false negatives.

An ECG signal is used to capture and document the cardiac rhythm and electrical activities of the heart [7]. These signals can be used to assess symptoms such as breathing difficulties, tachycardia, and chest pain, which may suggest the presence of a cardiovascular ailment. Additionally, it serves as a crucial clinical resource for diagnosing and treating heart-related diseases. Consequently, ECG equipment is currently widely used by all medical practitioners [8]. Inaccurate interpretation of ECG data due to its low quality may lead to a delay in medical intervention or possibly fatal consequences. Hence, acquiring a high-fidelity ECG signal is crucial for prompt and precise diagnosis, which facilitates effective patient treatment. To address the issue of subpar ECG quality, medical practitioners can employ a superior ECG electrode and a noise-reducing filter.

The primary issue impacting the ECG in this study is the elimination of noise from the ECG signal [7,8]. The alternating current supply generates electromagnetic interference, which causes PLI. This interference produces noise at a frequency of either 50 Hz or 60 Hz [9,10]. Additionally, respiration causes BW artefacts, while muscle electrical activity's EMG signal can directly disrupt the ECG signal [10]. Finally, the patient's movement is the root cause of motion artifacts, which manifest as shaking. Hence, it is imperative to minimise all forms of noise to acquire ECG signals of superior quality.

2. LITERATURE REVIEW

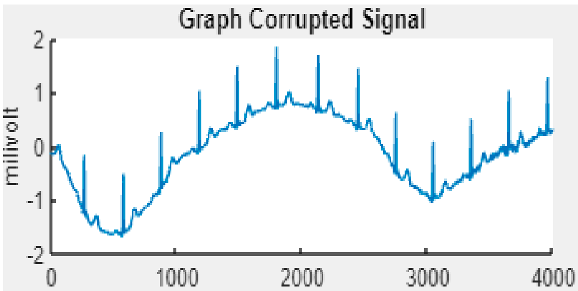
Applications that involve the cancellation of noise extensively employ adaptive filtering. Kose et al. employed adaptive filter-based algorithms, specifically the least mean square (LMS) and recursive least square (RLS) methods, to effectively eliminate EMG noise [1]. Both BW and PLI contribute to the interference present in the ECG signal. The filters' performance is evaluated by comparing their fidelity using the following parameters: MSE, normalised root mean squared error (NRMSE), signal-to-noise ratio (SNR), percentage root mean squared difference (PRD), and maximum error (ME). Shaddeli et al. employed an adaptive filter with the LMS method to mitigate the effects of BW and PLI on the ECG signal [2]. The researchers in the study used particle swap optimisation (PSO) and genetic algorithms (GA) in conjunction with an AF-based filter to improve AF's performance.

Bai et al. discovered that motion artifact noises frequently had significant baseline drift, also known as baseline wander [7]. AF was employed in the investigation to eliminate any interference caused by MA and BW. The noise reference signal is derived from the 3-axis acceleration signal. The findings indicated that the QRS complex was discernible and that any deviations in the baseline and disturbances caused by movement had been eliminated from the filtered ECG. Rajani Kumari et al. [8] conducted experiments that demonstrate the superior performance of the suggested pattern-adapted wavelet method compared to Symlet4 and other existing methodologies. A unique wavelet was developed utilising the least squares optimisation technique to meet the requirements of the Continuous Wavelet Transform (CWT) and accurately approximate the specified R-peak pattern of the ECG data. The method employs a wavelet-specific characteristic that computes the Continuous Wavelet Transform (CWT) coefficients of a signal precisely at its peak, provided that a local minimum and maximum pair are present.

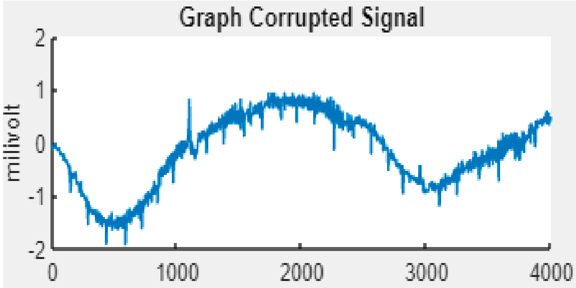
Kumar et al. proposed the use of the stationary wavelet transform to eliminate external interference-affected noise from an ECG signal [11]. Furthermore, this study also investigates other denoising techniques, such as the Fourier decomposition method, empirical mode decomposition, high-pass and low-pass filtering, and discrete wavelet transform. The signal-to-noise ratio, root mean square error, and percentage root mean square difference are utilised for comparing the denoising efficacy of ECG signals.

3. METHODOLOGY

The primary sources of contamination that have the greatest impact on the ECG are the BW, PLI, MA, and EMG interferences. An advantageous aspect is the absence of any association between the ECG signal and the BW, PLI, and EMG noises, facilitating a clear differentiation between the two. However, the complete overlap of the MA noise spectrum with the ECG signal made its elimination challenging. Baseline wander refers to the slow and erratic movement of the baseline. Various factors can affect the ECG signal. This mask's main effect is to hide ECG complexes like the T, QRS, and P waves, making it harder to see their unique peaks and troughs. Consequently, accurately detecting the specific time, magnitude, and configuration of different ECG features may provide greater difficulty as shown in Fig. 1 for both normal and AF signal [12].



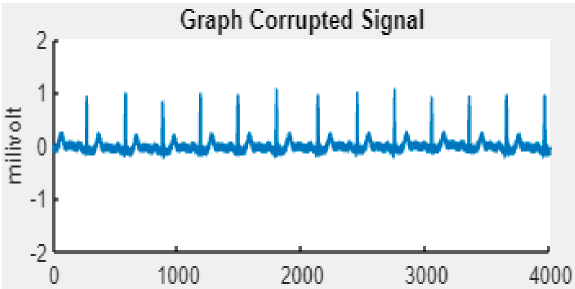
(a)



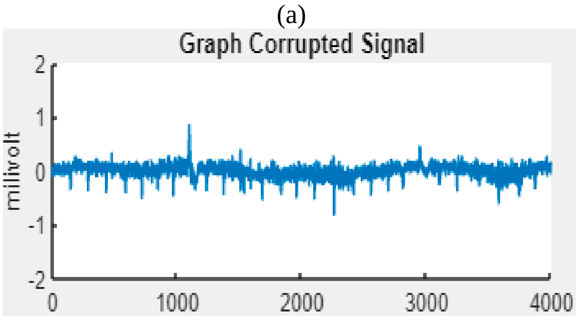
(b)

Fig. 1. Baseline wander contaminating in a) normal signal, b) AF.

Due to the presence of an interrupting voltage with a frequency of 50/60 Hz in the ECG, the identification of the PLI becomes more convenient. The interference may be attributed to the stray impact of alternating current fields generated by wire loops in the patient. Consider other notable factors such as contaminated or soiled electrodes and loose connections on the patient's wire. If the patient or the equipment are not properly grounded, power line interference can completely conceal the ECG signal as in Fig. 2 for both normal and AF signal [13].



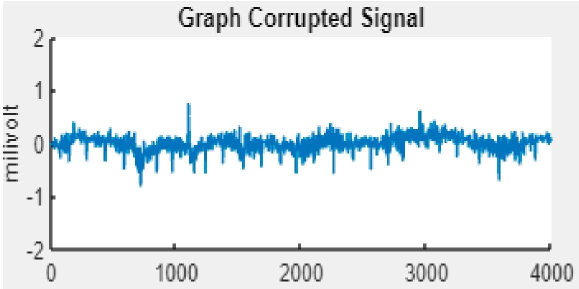
(a)



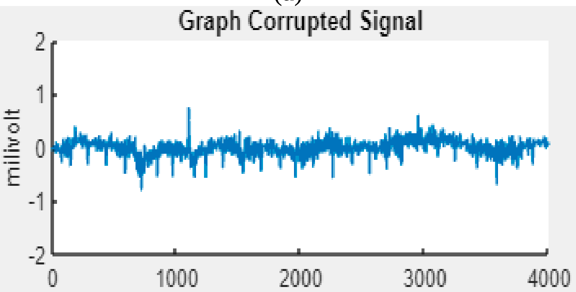
(b)

Fig. 2. Powerline interference contaminating in a) normal signal, b) AF.

ECG monitoring data may contain unexpected and unavoidable motion artifacts. Motion artefacts have historically plagued ECG measurements. The reason for the complete overlap of the P, QRS, and T peak components of the ECG signal and the spectrum of these disturbances is not solely due to chance. Reducing motion artifacts in the ECG signal is difficult and complex because it may result in information loss. Fig. 3 shows the ECG signal corrupted by motion artifact noise [14]. Last but not least, the EMG noise refers to disruptions or disturbances in the ECG caused by electrical activity in the skeletal muscles, which can distort the ECG signal. Muscle contractions are among the numerous possible reasons for EMG noise. The P wave, QRS complex, and T wave are the three primary components of the ECG waveform that can be altered by either suppressing or modifying their structure as in Fig. 4 [15].

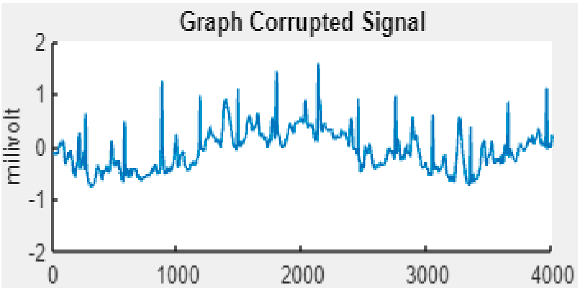


(a)

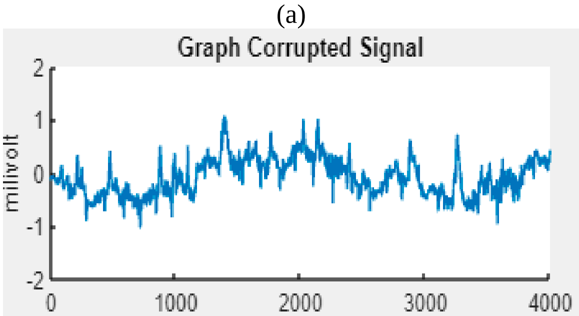


(b)

Fig.3. Motion artifact effect contaminating in a) normal signal, b) AF



(a)



(b)

Fig.4. Electromygram noise contaminating in a) normal signal, b) AF.

3.1 Adaptive Filter (Af)

An adaptive filter is a type of digital filter that automatically adjusts itself. By employing an adaptive method, the filter coefficients can be automatically adjusted to modify the input signal. Modern digital signal processing equipment employs adaptive filters for tasks like noise cancellation, adaptive control systems, active noise control, and biological signal augmentation [16, 17].

The Af structure is depicted in Fig. 5. The input signal is denoted as $x(p)$, whereas the reference signal is symbolised as $d(p)$ The input signal will undergo filtering using the filter coefficient w_p, and the resulting signal will be compared to the reference signal. $e(p)$ represents the discrepancy between the desired signal and the filter's output, whereas w_p denotes the factor used to adjust the filter coefficient. The process is iterated until the signal terminates. The updated filter coefficient is anticipated one step ahead of time by multiplying the system error $e(p)$, the current filter coefficient, and the system input $x(p)$.

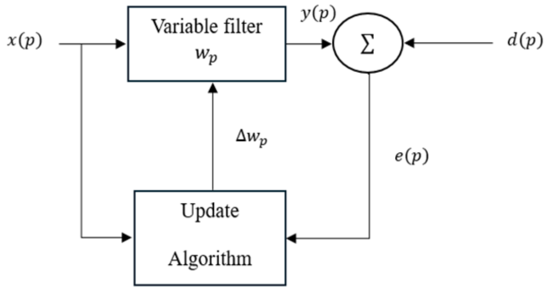


Fig. 5. Af block set

3.2 Discrete Wavelet Transform (DWT)

The DWT is a frequently employed wavelet transform method for reducing noise in ECG readings. In numerical and functional analysis, "DWT" refers to any wavelet transform that samples the wavelets discreetly [18]. It captures data on both frequency and position, providing a significant advantage in temporal resolution compared to the Fourier transform and other wavelet transforms. The wavelet analysis method utilises a wavelet prototype function known as the mother wavelet. In temporal analysis, a dilated wavelet with low-frequency characteristics is used, while in frequency analysis, a constricted wavelet with high-frequency characteristics is employed. In order to obtain the DWT of signal x, it undergoes a sequence of filtering operations. Fig. 6 displays the structure of the wavelet transformation [19].

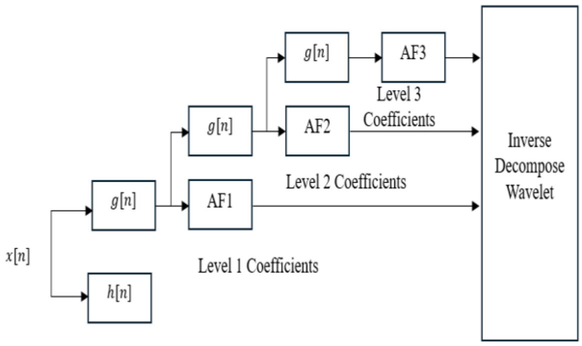


Fig. 6. Structure of wavelet transform

The samples are initially passed through a low pass filter with an impulse response of g, resulting in a convolution of the two signals. The signal is simultaneously analysed using a high pass filter, resulting in the extraction of the detail and approximation coefficients from the filter's output. The link between the two filters is significant. However, since half of the signal frequencies have been removed, it is possible to discard half of the samples. Next, employing Mallat's and the conventional nomenclature, the output of the filter is down sampled by a factor of two: g denotes a high-pass filter and h denotes a low-pass filter.

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k]$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$$

This decomposition has effectively halved the time resolution, as the signal now only includes half of each filter output feature. By reducing the subsampling operator, each output now has a frequency band that is half the size of the input, resulting in a doubled frequency resolution.

4. RESULT & DISCUSSION

To remove the influence of primary noises such as BW, PLI, MA, and EMG from the ECG signal, it is recommended to use filters that are based on DWT, Af, or a combination of DWT and Af. The MATLAB simulation software is used to create the desired simulation and apply it to the corrupted ECG data. The research suggests that both Af and DWT-based filters possess both benefits and drawbacks.

Af-based filters use the signal as a reference, enabling them to efficiently diminish uncorrelated noise. However, the Af-based filter failed to remove the correlated noise because its frequency range completely overlapped with the ECG signal. Therefore, to decrease the impact of noise on the ECG signal, filters based on DWT are used. Furthermore, the research indicates that AF-based filters effectively reduce low-frequency signals, while DWT-based filters may attenuate high-frequency sounds. The following studies demonstrate the efficacy of the filters in reducing extraneous ECG signal interference.

In order to implement the WT-based filter, this study employed the Sqtwolog, Rigrsure, Heursure, and Minimax thresholding algorithms. The AF-based filter, on the other hand, used the following algorithms in a certain order: RLS, LMS, normalised least mean square (NLMS), proportionate normalised least mean square (PNLMS), improved proportionate normalised least mean square (IPNLMS), and micro proportionate normalised least mean square (MPNLMS). After assessing the efficiency of each of these techniques, the SNR is measured. By combining Af-DWT-based filters, it is possible to evaluate the effectiveness of a bot filter in eliminating both high- and low-frequency noise concurrently. BW wander refers to the presence of low-frequency variance, or baseline drift, in an ECG signal. The sound normally occurs within the frequency range of 0 to 0.5 Hz. Typically, BW is attributed to the ECG measurement instrument.

Table 1. Baseline wander filtering performance

Type of filter used	SNR value (dB)
Normal ECG signal	
DWT (Minimax)	-25.49
Af (RLS)	13.84
DWT+Af (RLS)	39.48
AF ECG signal	
DWT (Rigrsure)	-29.53
Af (RLS)	8.96
DWT+Af (RLS)	16.86

The positioning of electrodes on various body areas can lead to EMG noise. Due to the placement of each electrode in a different location, the surrounding EMG noise is unique and not related to each other. EMG noise is commonly referred to as skin effect noise as tabled in Table 2.

Table 2. EMG removing performance

Type of filter used	SNR value (dB)
Normal ECG signal	
DWT (Minimax)	-16.13
Af (RLS)	16.57
DWT+Af (RLS)	26.91
AF ECG signal	
DWT (Rigrsure)	-20.09
Af (RLS)	11.35
DWT+Af (RLS)	16.26

The PLI widely refers to the electrical interference present in the power line source. In most cases, the frequency of this noise is somewhere between 50 and 60 Hz; however, it can vary somewhat depending on the power source that is used in each country. Table 3 shows the performance of filters to remove PLI.

Table 3. PLI eliminating performance

Type of filter used	SNR value (dB)
Normal ECG signal	
DWT (Minimax)	41.86
Af (RLS)	75.27
DWT+Af (RLS)	38.88
AF ECG signal	
DWT (Rigrsure)	15.17
Af (RLS)	53.03
DWT+Af (RLS)	40.61

Shaking of rhythmic movement leads to the occurrence of motion artefacts. Patients exhibiting limb movement during the test exemplify motion artefacts, leading to sudden anomalies in the ECG baseline. Therefore, it is the most formidable noise in the ECG signal. Motion artifact have been removed from ECG signal by using filters and the results are tabled in Table 4.

Table 4. Motion artifact reducing performance

Type of filter used	SNR value (dB)
Normal ECG signal	
DWT (Minimax)	7.32
Adaptive Filter (RLS)	33.71
DWT+AF (RLS)	31.45
AF ECG signal	
DWT (Rigrsure)	6.25
Adaptive Filter (RLS)	21.59
DWT+AF (RLS)	21.43

5. CONCLUSION

This study effectively employed adaptive filter and wavelet transform techniques to efficiently remove noise from ECG data through comprehensive examination and implementation. The study's findings revealed a significant reduction in noise levels without compromising the integrity of the signal, highlighting the effectiveness of these strategies in improving diagnosis accuracy. In addition, the wavelet transform-adaptive filter successfully integrated and showcased its ability to innovate and modify existing methods to enhance denoising efficiency. Based on the research findings, these integrated methods outperformed standalone methods, emphasizing the importance of collaboration in signal processing applications. Lastly, the results showed that the wavelet transform-adaptive filter and adaptive filter-wavelet transform methods worked better than the others, showing that they were better at removing noise.

By using a proficient denoising technique is essential to acquire an ECG signal that is devoid of any interference. Nevertheless, it is imperative to reduce substantial interference that impacts the ECG signal, such as BW, PLI, MA, and EMG effects with the measurement is best in range of 20 to 30 of SNR dB. DWT based filters, Af based filters, and combinations of DWT-Af based filters are all suggested as ways to get rid of things. Filters based on the DWT, Af, and DWT-Af were successfully created using the MATLAB simulation tools with 16.86 dB for BW, 16.26 for EMG, 40.61 for PLI and 21.43 dB for MA, removing noise from AF signal. For normal ECG signal the best filtered result are 39.48 dB for BW, 26.91 for EMG, 38.88 for PLI and 31.45 dB for MA,

The results suggest that both Af and DWT filters have limitations, with Af filters being more effective at attenuating low frequencies and DWT filters being proficient at suppressing high frequencies. The amalgamation of the two fundamental filters exhibits superior performance in effectively eliminating both high- and low-frequency noise simultaneously. Here are a few recommendations for DWT: Given the current confinement of the study to Daubechies's mother wavelets, it would be beneficial to explore several types of mother wavelets. Although this study only uses RLS and LMS based adaptive filters, a range of Af based filters may be suitable for future applications.

Further studies have the potential to improve specific features of the ECG waveform. Consider the QRS complex or the ST segment. Methods such as morphological filtering, matched filtering, and neural network classification can be employed to improve waveform components.

6. REFERENCES

[1] S. H. Marwan, M. Todo, Biomechanical analysis of hypertrophic cardiomyopathy behavior of human heart using dynamic finite element method. Proceeding of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 5 (2019) 60-62.

[2] R. Shaddeli, N. Yazdanjue, S. Ebadollahi, M. M. Saberi, B. Gill, Noise removal from ECG signals by adaptive filter based on variable step size LMS using evolutionary algorithms. In 2021 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE) (2021) 1-7.

[3] W. A. Al Madhoun, M. H. Abu Hamda, Y. I. Al Jeesh, H. Kim, G. M. Hosang, Assessment of Noise Exposure Impacts on Blood Pressure and Pulse Rate at Intensive Care Units in Gaza Strip-Palestine. Proceeding of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 3 (2017) 60-62.

[4] M. B. Tayel, A. S. Eltrass, A. I. Ammar, A new multi-stage combined kernel filtering approach for ECG noise removal. Journal of Electrocardiology. 51(2) (2018) 265-275.

[5] H. D. Hesar, M. Maryam, An adaptive Kalman filter bank for ECG denoising. Journal of Biomedical & Health Informatics. 25(1) (2020) 13-21.

[6] X. Wang, Y. Zhou, M. Shu, Y. Wang, A. Dong. ECG baseline wander correction and denoising based on sparsity." IEEE Access. 7 (2019) 31573-31585.

[7] L. M. Bai, M. H. Fan, C. H. Feng, L. H. Wang, Using an adaptive filter to remove ECG motion artifact interference. In 2018 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW) (2018) 1-2.

[8] L. V. Rajani Kumari, Y. Padma Sai, N. Balaji, (2023). R-peak identification in ECG signals using pattern-adapted wavelet technique. IETE Journal of Research, 69(5) (2023) 2468-2477.

[9] M. B. Hossain, S. K. Bashar, J. Lazaro, A robust ECG denoising technique using variable frequency complex, Computer Methods & Programs in Biomedicine, 200 (2021) 105856.

[10] H. T. Chiang, Y. Y. Hsieh, S. W. Fu, K. H. Hung, Y. Tsao, S. Y. Chien, Noise reduction in ECG signals using fully convolutional denoising autoencoders. IEEE Access. 7 (2019) 60806-60813.

[11] A. Kumar, H. Tomar, V. K. Mehla, R. Komaragiri, M. Kumar, (2021). Stationary wavelet transform based ECG signal denoising method. ISA Transactions, 114 (2021) 251-262.

[12] F. D. Romero, D. C. Piñol, C. R. Vázquez-Seisdedos. DeepFilter: An ECG baseline wander removal filter using deep learning techniques. Biomedical Signal Processing & Control. 70 (2021) 102992.

[13] C. Binqiang, Y. Li, X. Cao, W. Sun, W. He. Removal of power line interference from ECG signals using adaptive notch filters of sharp resolution. IEEE Access. 7 (2019) 150667-150676.

[14] S. Dongyeol, S. Lee, M. Kim, J. Cho, C. Kim. Motion artifact removal techniques for wearable EEG and PPG sensor systems. Frontiers in Electronics 2 (2021) 685513.

[15] M. Mortezaee, Z. Mortezaie, V. Abolghasemi. An improved SSA-based technique for EMG removal from ECG. Irbm 40(1) (2019) 62-68.

[16] F. R. Hashim, J. J. Soraghan, L. Petropoulakis, N. G. N. Daud. EMG cancellation from ECG signals using modified NLMS adaptive filters. In 2014

IEEE Conference on Biomedical Engineering and Sciences (IECBES), (2014) 735-739.

[17] H. Fuyi, J. Zhang, S. Zhang. A family of robust adaptive filtering algorithms based on sigmoid cost. Signal Processing. 149 (2018) 179-192.

[18] J. Adnan, N. G. N. Daud, S. Ahmad, M. H. Mat, M. T. Ishak, F. R. Hashim, M. M. Ibrahim. Heart abnormality activity detection using multilayer perceptron (MLP) network. In AIP Conference Proceedings. 2016(1) (2018).

[19] S. Amit, P. Singh, B. Fatimah, R. B. Pachori. An efficient removal of power-line interference and baseline wander from ECG signals by employing Fourier decomposition technique. Biomedical Signal Processing & Control. 57 (2020) 101741.