ECG SIGNAL DENOISE USING WAVELET ADAPTIVE FILTER

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

Siti Noormiza Makhtar
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/10.5109/7395537

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 11, pp.331-336, 2025-10-30. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：

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Nur Izzani Mat Rozi[1], Siti Noormiza Makhtar[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
izzani299@gmail.com

Abstract: *The research evaluates how integrating discrete wavelet transform (DWT) with adaptive filters (A-F) enhances the reduction of electrocardiogram (ECG) signal noise. The correct interpretation of heart diseases through ECG signals depends heavily on signal quality because multiple noise types can affect the signals. Powerline interference (PLI) together with motion artifacts (MA) and baseline wander (BW) and electromyogram (EMG) interference constitute the noise sources affecting electrocardiogram (ECG) signals. This interference can either be correlated or uncorrelated. Noises must be eliminated because they create diagnostic inaccuracy and unreliability. The study develops an AF-WT-based filter system to solve this issue. This research evaluates the DWT and A-F based filter against standard DWT and A-F for signal processing. The DWT and A-F besd filter produces an acceptable signal to noise ration (SNR) while simultaneously removing all major ECG signal distortions including PLI, MA, BW and EMG noise thus showing promise for diagnostic accuracy enhancement.*

Keywords: electrocardiogram; diagnosing; interference; filtering; construct

1. INTRODUCTION

Atrial fibrillation (AF) exists when cardiac rhythms become irregular with rapid heart beat patterns. An irregular heartbeat with a medical name of arrhythmia exists according to [1]. Among the 183,321 death certificates from 2019 AF was listed as the primary cause of 26,535 fatalities. The number of AF cases increases steadily as people grow older [2]. Besides age-related factors AF can develop due to obesity or smoking as well as hypertension. Better prediction algorithms hold promise to enhance Af therapy and lower the number of new Af patients. The early start of treatment enables better predictions about AF commencement which can prevent deaths. Numerous people overlook these symptoms of AF including tachycardia and dyspnea and vertigo although the condition is present [2].

The development of a new ECG analysis system serves as a critical necessity to generate initial data that helps detect AF at its onset. The system has two processing units which handle signal decomposition and signal filtering. Different noise cancellation methods were used to remove individual disturbances within the ECG signal due to its excessive noise content. Most technical issues in ECG signal processing stem from the noise which pollutes the ECG signal. The ECG signal hosts four primary kinds of noise including BW [3], PLI [4], EMG [5] and MA [6]. Standard digital filters successfully eliminate disturbances which exist independently from the main signal as well as BM and PLI and EMG. The removal of noises produced by skeletal muscle activity through MA proves difficult since their frequency spectrum overlaps completely with ECG signal frequencies. The choice of an inappropriate filter leads to information degradation in the ECG signal while decreasing noise levels. The analysis methods can produce incorrect findings that result in either incorrect positive or negative results.

The ECG signal functions to record heart electrical activities together with cardiac rhythm for documentation purposes [7]. The detected signals help healthcare providers identify symptoms that include shortness of breath, rapid heart rate and chest pain to determine cardiovascular disease possibilities.

Heart-related diseases receive vital clinical diagnosis and treatment from this system. ECG equipment is widely utilized by medical practitioners across all sectors of the field according to literature [8]. The interpretation of ECG data becomes ineffective when its quality is poor which results in delayed medical care or even dangerous outcomes. The success of quick and accurate medical diagnosis heavily depends on obtaining high-quality ECG signals to provide effective treatment for patients. Medical practitioners should use better ECG electrodes together with noise reduction filters as solutions to enhance ECG signal quality.

The main problem affecting ECG data in this research involves noise elimination from the ECG signal [7,8]. The alternating current supply creates electromagnetic interference that results in PLI. The interferences emit noise frequencies of 50 or 60 Hz [9-10]. The ECG signal experiences direct interference from EMG signals that generate muscle electrical activity and creates BW artefacts during respiration [10]. Patient movement causes motion artifacts that result in shaking as the primary source. Acquiring ECG signals of better quality demands complete noise reduction.

2. LITERATURE REVIEW

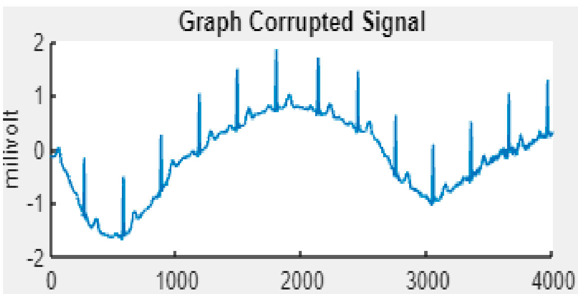
The extensive use of adaptive filtering occurs in applications that require noise cancellation. The research by Kose et al. used adaptive filter (A-F) based algorithms where least mean square (LMS) and recursive least square (RLS) methods served to remove EMG noise effectively [1]. The ECG signal contains interference elements that result from both BW and PLI. The performance evaluation of the filters includes an assessment of their fidelity through evaluation of mean square error (MSE) alongside SNR and mean absolute error (MAE). The researchers at Shaddeli et al. used an adaptive filter operated by the LMS method to reduce BW and PLI interference in ECG signals [2]. Researchers employed A-F based filters with genetic algorithm and particle swarm optimization algorithms to enhance A-F functionality in their investigation.

According to Bai et al. motion artifact noises exhibit major baseline drift known as baseline wander [7]. The researchers used A-F as a tool to remove any electrical noise that might come from MA and BW. A noise reference signal originates from the 3-axis acceleration signal. Research data showed both the QRS complex was clearly observable while baseline drift and movement-induced noise were eliminated from the filtered ECG. The research of Rajani Kumari et al. [8] presents experimental evidence which proves that the proposed pattern-adapted wavelet method achieves better results than Symlet4 and other conventional methods. The Continuous Wavelet Transform (CWT) required a special wavelet which was developed through least squares optimization to precisely match the specified R-peak pattern of ECG data. The method achieves precise CWT coefficient computation through its wavelet-specific feature which operates at the signal peak with the existence of local minimum-maximum pairs.

The stationary wavelet transform serves as a noise removal approach for ECG signals according to Kumar et al. [11]. The study examines various denoising methods including Fourier decomposition, empirical mode decomposition along with high-pass and low-pass filtering and discrete wavelet transform in addition to its investigation. Researhers compare ECG signal denoising effectiveness by using three measurement methods which include SNR and MSE.

3. METHODOLOGY

Among all sources of ECG contamination the BW, PLI, MA, and EMG interferences prove most detrimental to the ECG signal quality. The lack of relation between ECG signals and BW and PLI and EMG noise provides a clear separation between the two signals. The total spectrum of MA noise proved difficult to eliminate because it completely matched the ECG signal. The normal and erratic movement of the baseline constitutes baseline wander. Multiple elements exist that influence the characteristics of ECG signal. The main outcome of this mask is the concealment of ECG complex waves including T, QRS and P waves which reduces observer visibility of their characteristic peaks and troughs. The precise identification of times and characteristics for different ECG features proves harder due to the examples in Fig. 1 for normal and AF signals [12].



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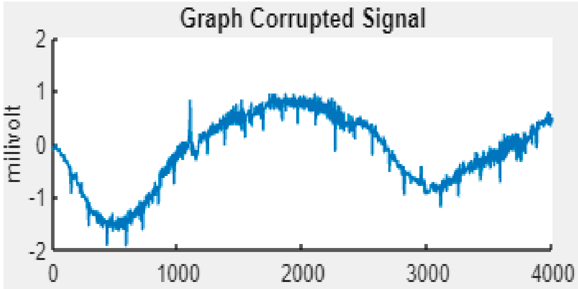
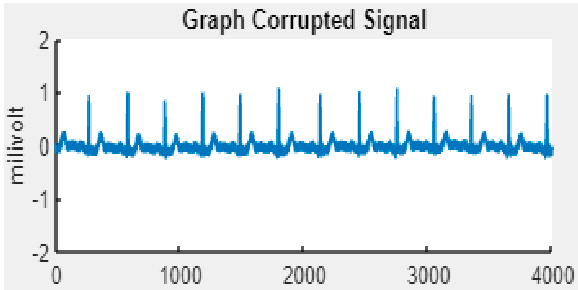


(b)

Fig. 1. BW 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].



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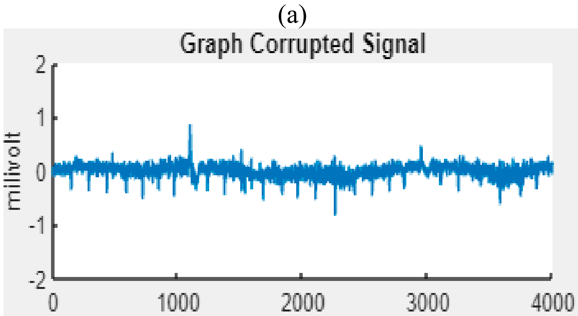
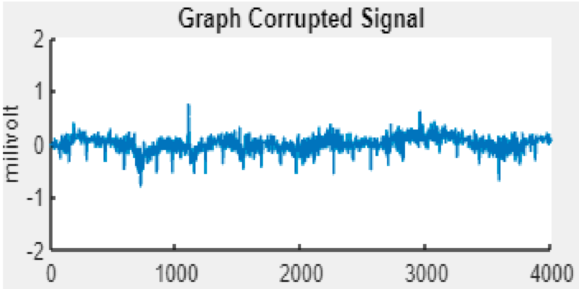


(b)

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

Uncontrollable unexpected MA can appear in ECG monitoring data. ECG measurements have suffered from MA for many years. The total fusion of ECG signal P, QRS, and T peak components with these disturbances does not occur randomly. ECG signal artifact reduction presents both complexity and difficulty because such process could lead to information loss. Fig. 3 illustrates an ECG signal contaminated by motion artifact noise [14]. The final category of noise in ECG measurements is EMG noise which appears when electrical muscle activity generates disturbances that distort the ECG signal. EMG noise emerges from various forms of muscle contractions which represent potential causes among multiple others. The three main ECG waveform elements including P wave, QRS complex, and T wave show structural changes when such alterations occur as depicted in Fig. 4 [15].



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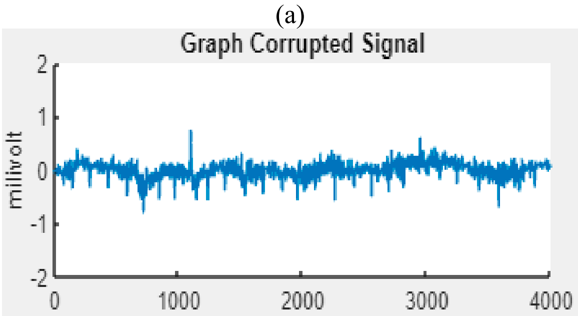

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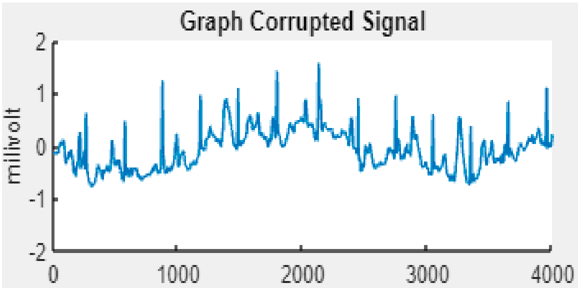
Fig. 3. MA contaminating in a) normal signal, b) AF



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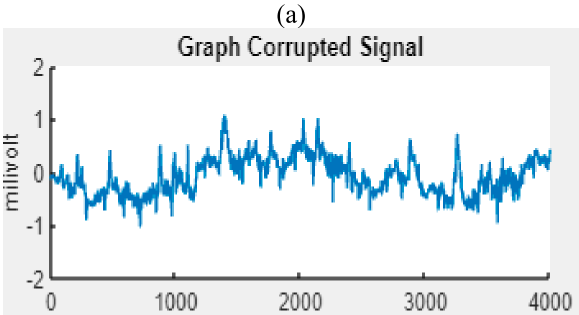

(b)

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

3.1 Adaptive Filter (A-F)

The digital filter known as an A-F maintains automatic adjustments to its operation. Through adaptive methods the input signal can be modified by automatic coefficient adjustments. Digital signal processing equipment uses A-F to perform noise cancellation and adaptive control systems and active noise control and biological signal augmentation [16-18].

The diagram of A-F structure appears in Fig. 5. The $x(p)$, represents the input signal while $d(p)$ symbolizes the reference signal. The filtering process applied to $x(p)$ by Δwp leads to a comparison with $d(p)$. The discrepancy between these signals appears as $e(p)$ and w_p controls the adjustment of the filter coefficient. The signal processing continues until the signal finishes. The updated filter coefficient can be projected one step ahead based on the system error $e(p)$, by multiplying it with the existing filter coefficient and the system input $x(p)$.

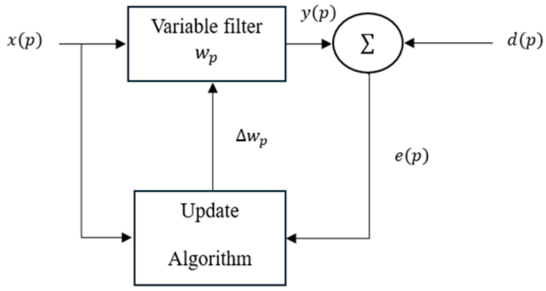

Fig. 5. A-F block set

3.2 Discrete Wavelet Transform (DWT)

DWT stands as one of the most common wavelet transforms used to diminish noise in ECG measurements. Numerical and functional analysis define "DWT" as any wavelet transform which samples wavelets through discrete measurements [19-20]. The DWT extracts information about spatial position and frequency making it superior to the Fourier transform and other wavelet transforms in its ability to determine temporal resolution. The wavelet analysis procedure uses a mother wavelet prototype function as its basis. Either a dilated wavelet with lower frequency properties or a constricted wavelet with higher frequency properties serves for either temporal or frequency analysis. The signal x needs to go through a series of filtering operations for obtaining its DWT. Fig. 6 displays the structure of the wavelet transformation [21].

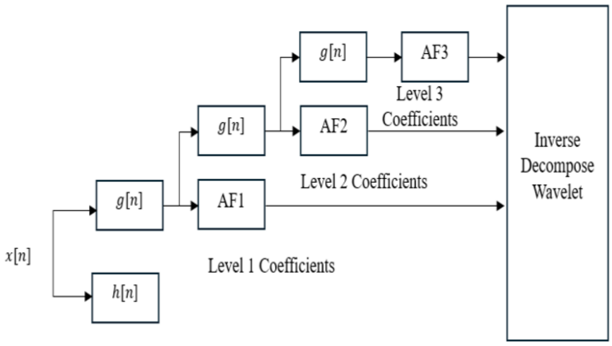

Fig. 6. Structure of WT

The low pass filter with impulse response g convolves two signals to produce the output samples. The high pass filter analysis of the signal generates detail and approximation coefficients from its output. The connection between the two filters holds great importance. The removal of fifty percent of signal frequencies enables us to delete fifty percent of the samples. The output signal of the filter undergoes down sampling by a factor of two according to both Mallat's and conventional nomenclature while low-pass filter h and high-pass filter g operate sequentially.

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

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

The decomposition process has cut the time resolution by half because the signal now includes only half of each filter output feature. Each output frequency band obtains half the size of the input bands after subsampling reduction thus achieving double frequency resolution.

4. RESULT & DISCUSSION

The removal of primary ECG signal noises such as BW, PLI, MA and EMG requires filters built with DWT, A-F or their integration. The MATLAB simulation software serves as a platform to develop the simulation model after which it is applied to process corrupted ECG data. The research demonstrates that filters applying DWT and A-F technology present both positive and negative aspects.

The reference signal function of A-F based filters lets them perform effective noise reduction on uncorrelated disturbances. The frequency range of the A-F based filter extended throughout the entire ECG signal spectrum preventing it from eliminating the correlated noise. The application of DWT-based filters becomes essential for reducing noise effects on the ECG signal. The research findings show A-F based filters excel at blocking low-frequency sounds but DWT-based filters demonstrate some capacity to block high-frequency signals. The subsequent studies show that filters decrease extraneous ECG signal interference effectively.

This research adopted the Sqtwolog and Rigrsure and Heursure and Minimax thresholding algorithms to construct the DWT based filter. The A-F based filter executed its algorithms starting with RLS followed by LMS then normalised least mean square (NLMS) after which proportionate normalised least mean square (PNLMS) ran before improved proportionate normalised least mean square (IPNLMS) and finishing with micro proportionate normalised least mean square (MPNLMS). The SNR measurements take place following the efficiency evaluation of these approaches. The combination of A-F and DWT based filters enables users to determine how well bot filters perform at removing both low-frequency and high-frequency noise. A signal shows BW wander when it contains low-frequency variance that results in baseline drift. The sound occurs within frequencies between 0 and 0.5 Hz. The ECG measurement instrument usually causes BW issues.

Table 1. BW wander filtering performance using Sqtwolog threshold and LMS filtering

Type of filter used	SNR value (dB)
Normal ECG signal	
DWT	-25.49
A-F	0.48
DWT+A-F	5.76
AF ECG signal	
DWT	-19.53
A-F	4.69
DWT+A-F	6.68

EMG noise arises from different placements of electrodes on the body surface. Each electrode creates distinct EMG noise since they are placed in separate body locations which makes them unrelated to each other. EMG noise obtains its name from skin effect and this information appears in Table 2.

Table 2. EMG removing performance using Sqtwolog threshold and LMS filtering

Type of filter used	SNR value (dB)
Normal ECG signal	
DWT	-16.13
A-F	15.51
DWT+A-F	5.77
AF ECG signal	
DWT	-21.89
A-F	9.21
DWT+A-F	12.62

PLI represents the electrical disturbances that exist in power line sources according to the PLI description. The typical range of PLI frequency appears between 50-60 Hz, but countries use different power sources to generate slight variations in noise frequencies. Results regarding PLI removal through filtering appear in Table 3.

Table 3. PLI eliminating performance using Sqtwolog threshold and LMS filtering

Type of filter used	SNR value (dB)
Normal ECG signal	
DWT	30.92
A-F	29.17
DWT+A-F	35.15
AF ECG signal	
DWT	12.17
A-F	36.03
DWT+A-F	32.61

When a person experience a rhythmic shaking motion the resulting effect is known as MA. The movement of patient limbs causes MA that result in sudden irregularities of the ECG baseline. Among all noises inside ECG signals this form of interference represents the most difficult to remove disturbance. The removal of MA from ECG signals was achieved by implementing filter techniques while Table 4 displays the obtained results.

Table 4. MA artifact reducing performance using Sqtwolog threshold and LMS filtering

Type of filter used	SNR value (dB)
Normal ECG signal	
DWT	12.37
A-F	33.71
DWT+A-F	21.67
AF ECG signal	
DWT	0.52
A-F	15.95
DWT+A-F	21.34

An ECG acquisition process requires proficient denoising tools to eliminate all types of interference from the signal. The ECG signal measurement should maintain its best quality between 20 and 30 dB of SNR for acceptable reduction of major signal interference including BW, PLI, MA and EMG effects. DWT based filters together with A-F based filters along with combination of DWT and A-F based filters represent proposed approaches to eliminate noise. Simulation tools in MATLAB successfully generated the filters which employed DWT, A-F and combined DWT and A-F based filter with results showing 6.68 dB for BW and 12.62 dB for EMG followed by 32.61 dB for PLI and 21.34 dB for MA, effectively removing noise from AF signal. The most effective signal output for normal ECG signals through filtering shows 5.76 dB BW and 5.77 dB EMG and 35.15 dB PLI along with 21.67 dB MA.

The research indicates that AF filters display better effectiveness toward low frequency signals but DWT filters demonstrate superior performance in eliminating high frequency signals. The combination of core filters shows peak performance by eliminating high-frequency and low-frequency noise together efficiently. The research investigation are rely on RLS and LMS of A-Fs but researchers should study various AF filters which could prove applicable for future development. In addition, more research on the ability to enhance particular features within ECG waveforms. Researchers should analyse both the QRS complex and the ST segment. The improvement of waveform components can be achieved through the use of filtering method as well as matched filtering and neural network classification techniques.

5. CONCLUSION

This study applied A-F and DWT based filters to fully examine and implement noise reduction for ECG data effectively. The research proved that these approaches successfully decreased contaminated noises in ECG signals without removing the original signal information thus demonstrating their effectiveness for enhancing filtering results. The combined DWT and A-F based filter successfully demonstrated its capability for method enhancement through integration and innovation of existing techniques for improved denoising performance. Research outcomes demonstrated that integrated methods provided superior performance results compared to individual methods because signal processing benefits from integrated approaches.

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