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Comparison on Wavelet Adaptive Filter Performance in Denoising ECG Signal

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ABSTRACT

Heart failure has sped up the development of electrocardiogram (ECG) signal denoising techniques. Researchers have developed a workable method to reduce the impact of noise in the ECG data, which can help avoid incorrect diagnoses and unnecessary medical procedures because heart failure can lead to fatal. Obtaining a clean ECG signal requires the use of an exact denoising process, which includes feature extraction, filtering, and pattern identification. To ensure the accuracy and reliability of the ECG signal, it is necessary to eliminate significant sources of noise, including baseline wander (BW), powerline interference (PLI), motion artifact (MA), and electromyogram (EMG). The study suggests that the filtering stage should utilise filters that are based on adaptive filters (AF). AF has the capacity to automatically update its filter coefficients in response to variations in the input signal and will keep updated the filter coefficient to minimise the error. The design of the AF and the performance comparison observed in the signal to noise ratio (SNR) test will be conducted utilising the MATLAB simulation software. The findings indicate that combining decompose wavelet transform (DWT) and adaptive filter (AF) may improve performance compared to DWT and AF alone. The best combinations to reduce noise signals from ECG are 30.01 dB, 29.67 dB, 23.72 dB, and 28.31 dB for BW, PLI, EMG, and MA, respectively.

1. Introduction

The importance of this study arises from its potential to improve the precision and reliability of electrocardiogram (ECG) signal interpretation by utilising recent denoising techniques. The ECG is a vital diagnostic tool for monitoring and identifying heart issues. However, ECG measurements are typically distorted by noise from a variety of sources, such as muscle activity, electrode movement, and power line interference, which can distort essential diagnostic information. This project will create and verify an advanced denoising algorithm to discover the type of filter that effectively

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reduces the effects of noise in ECG readings. Better signal quality enables more accurate detection of cardiac anomalies, resulting in better patient outcomes. The analysis of electrocardiogram (ECG) data is the study's main objective. The study uses several methods to improve the ECG signal's quality, including filtering, feature extraction, and pattern recognition. These methods are frequently employed in biomedical engineering to analyse and handle ECG data. It is emphasised how crucial correct ECG signal analysis is. An accurate diagnosis is necessary because any errors in interpreting the ECG data could cause therapy to be delayed or ineffective, which could have serious consequences for the patient. The goal of the study is to remove interference from the ECG signal to prevent the issues outlined before. Any unwanted signals or noise that muddles the original ECG waveform and make it difficult to interpret correctly is referred to interference.

Subsequently, the ECG signal may contain a few types of interference, including baseline wander (BW) taken from [1], powerline interference (PLI) taken from [2], motion artefact (MA) taken from [3], and electromyogram (EMG) taken from [4]. While PLI is an electrical noise at the powerline frequency (often 50 or 60 Hz) that can distort the ECG signal, BW is a steady drift of the baseline brought on by factors like patient movement or breathing. The EMG noise, on the other hand, is the interference brought by electrical activity in skeletal muscles that may cross over with the ECG signal. The MA noise is introduced because of the patient's movement during the ECG recording. The available literature has included a study on the topic of denoising ECG data. Adaptive filtering is a method for denoising that is frequently employed. The methods aid in decoupling noise from the ECG signal, producing a clearer and more trustworthy depiction. The paper probably depicts a preliminary design or method for ECG signal denoising that has since been enhanced by a few adjustments. These changes are intended to improve the system's capacity to efficiently filter out interference and generate high-quality ECG readings for precise analysis and diagnosis.

Adaptive filter was used in several applications for noise cancellation. Kose *et al.,* [5] used adaptive filter-based least mean square (LMS) and recursive least square (RLS) to remove EMG noise. For noise cancellation, adaptive filtering is frequently used in a variety of applications. Kose *et al.,*'s [5] work specifically targeted electromyogram (EMG) noise removal and used the recursive least square (RLS) and adaptive filter-based least mean square (LMS) adaptive filtering techniques. These adaptive filtering methods are crucial tools in biomedical engineering because they enable more precise and reliable data interpretation by removing undesired noise from signals. BW and PLI make up the noise in the ECG signal. Mean square error (MSE), normalized root means square error (NRMSE), signal-to-noise ratio (SNR), percentage root mean square difference (PRD) and maximum error (ME) are the fidelity characteristics used to evaluate the filter performance. In the electrocardiogram (ECG) signal, baseline wander (BW) and powerline interference (PLI) are two common types of noise. Researchers employ several fidelity measures to assess the efficacy of the adaptive filtering techniques outlined before. The mean square error (MSE), normalized root mean squared error (NRMSE), signal-to-noise ratio (SNR), percentage root mean squared difference (PRD), and maximum error (ME) serve as quantitative metrics to evaluate how well the adaptive filters reduce noise and preserve the essential characteristics of the original ECG signal. This thorough study helps researchers to choose the best adaptive filtering method for their unique noise cancelling needs.

The least-mean-square (LMS) approach and an adaptive filter, on the other hand, were used by Shaddeli *et al.,* [6] to diminish the BW and PLI effects in the ECG signal taken from. Researchers in the study used an AF-based filter with the Genetic Algorithm (GA) and Particle Swamp Optimization (PSO) methods to improve the performance of adaptive filters. On the other hand, in a different study by Shaddeli *et al.,* [6] the emphasis was on utilizing adaptive filtering in conjunction with the least-mean-square (LMS) method to reduce the effects of baseline wander (BW) and powerline interference (PLI) in the ECG signal taken from. The researchers combined the performance of the adaptive filtering with two cutting-edge methods: the Genetic Algorithm (GA) and Particle Swamp Optimization (PSO). These optimization techniques are used to precisely adjust the adaptive filter's parameters, resulting in improved ECG signal preservation and more accurate noise cancellation. The combination of optimization algorithms and adaptive filtering exemplifies the continuous efforts in biomedical engineering to create sophisticated methods for noise reduction in medical data.

In research by Bai *et al.,* [7] they uncovered the intriguing revelation that high baseline drift, often referred to as baseline wander, is frequently present along with motion artefact sounds in ECG data taken from. They used adaptive filtering techniques to efficiently eliminate baseline drift and motion artifacts from the ECG signals to solve this problem. The 3-axis acceleration signal was employed as the noise reference signal in their method. According to their study's findings, baseline drifts and motion artifacts from the filtered ECG signals were successfully removed, and the QRS complex—a crucial component of ECG analysis—became distinctly evident. This discovery shows that adaptive filtering can effectively enhance the quality of ECG signals that are distorted by motion artifact noise and baseline drift, enabling more precise ECG analysis and interpretation.

Moving on to another study by Kaleem and Kokate [8], their goal was to use multichannel ECG leads to differentiate between fetal ECG signals during pregnancy and labor. In this method, multichannel ECG leads were used to record electrical potentials on the mother's body surface. They were able to observe the electrical signals the fetal heart was producing by doing this. The interference from the mother's cardiac signal, which overlaps with the fetal signal and makes it difficult to accurately extract the fetal signal, is a substantial barrier in this process. The researchers used a potent and flexible filtering strategy in their research to get around this problem. This filtering method was created primarily to separate the fetus signal from the maternal cardiac signal's interference, allowing for a more accurate fetal ECG extraction. The researchers utilized the operational platform of MATLAB to carry out extensive testing to confirm the efficacy of their proposed approach. They carefully analyzed the test results, perhaps by comparing the retrieved fetal ECG signals to validated or known ground truth data to assess the precision and dependability of their filtering technique.

In other works, when compared to Symlet4 and other existing approaches, Kumari *et al.,*'s [9] experimental findings demonstrate that the suggested pattern-adapted wavelet method performs better. Using the least square optimisation technique, a new wavelet was created that not only approximates the provided R-peak pattern of the ECG signal but also complies with the requirements set forth by Continuous Wavelet Transform (CWT). The approach takes advantage of the wavelet-specific characteristic that computes the CWT coefficients of a given signal at the point of the signal peak where the local maximum and minimum pair exist. An ECG signal that has been tainted with noise can be denoised using the stationary wavelet transform, which Kumar *et al.,* [10] proposed in the paper taken from [7]. Other denoising techniques such as low-pass filtering, high-pass filtering, empirical mode decomposition, the Fourier decomposition method, and discrete wavelet transform are also investigated. ECG signal denoising performance is compared using the signal-to-noise ratio, percentage root-mean-square difference, and root mean square error.

According to Wang *et al.,* [1] the diagnosis is established in clinical practise by examining the ECG beat-by-beat. However, this is often tedious and time-consuming. In the research, they provide a Continuous Wavelet Transform (CWT) and Convolutional Neural Network (CNN)-based automated ECG categorization approach. CNN is used to extract features from the 2D-scalogram made up of the various time-frequency components obtained by CWT's decomposition of the ECG signals. In the other study, Yildirim employed long-short term memory networks (LSTMs), the most popular recurrent neural networks (RNNs) architecture and a new development in sequential data processing taken from [11]. Deep versions of these architectures have been successfully adapted, which has advanced the field of deep learning. In the research, a brand-new classifier for ECG data dubbed DBLSTM-WS was suggested for deep bidirectional LSTM network-based wavelet sequences. To do this, a new wavelet-based layer is put into use to produce ECG signal sequences.

Previous research indicates that both adaptive filters and wavelet transforms possess distinct advantages and disadvantages in reducing low-frequency and high-frequency noise. Furthermore, there occur two categories of noise: correlated and uncorrelated, which limit a single filter's performance in reducing noise effects. This work proposes the integration of adaptive filtering with wavelet transforms in order to reduce both low-frequency and high-frequency noise while maintaining the integrity of the original ECG signal.

2. Methodology

The major interferences that significantly affect the contamination of ECG signals are baseline wander (BW), powerline interference (PLI), motion artefact (MA), and electromyogram (EMG) interference [11]. It is simpler to distinguish between the BW, PLI, and EMG noises because there is no association between the ECG signal and these sounds. It is challenging to accurately differentiate the two, nevertheless, because the frequency spectrum of MA noise totally overlaps that of the ECG signal [11]. The phrase "baseline wander" refers to the sluggish, wavy motion of the baseline in the ECG signal. Numerous factors can contribute to baseline wander, which can obscure significant ECG complexes like the P wave, QRS complex, and T wave. This obscuration affects the ECG signal's timing, amplitude, and form analysis clarity, making it challenging to recognize and correctly identify the distinctive peaks and valleys that define these ECG features [12]. On the other hand, powerline interference (PLI) is more obvious since it frequently happens when a voltage frequency of 50/60 Hz interrupts the ECG signal [13]. This interference frequently results from stray effects of alternating current fields, which may be brought on by loose connections, loops in the patient's wiring, or dirty electrodes.

Furthermore, due to power line interference, incorrect grounding of either the patient or the medical equipment can completely obstruct the ECG signal. Baseline wander, powerline interference, motion artefacts, and electromyogram interference are all common sources of noise in ECG data. While motion artefact noise's overlapping frequency spectrum makes it difficult to precisely remove, baseline wander and powerline interference are rather easy to identify from the ECG signal. For accurate and clear ECG signals, which help with better medical diagnosis and well-informed treatment choices, these interferences must be recognised and appropriately dealt with. To improve ECG signal quality and contribute to better patient care, scientists and medical experts are still investigating advanced filtering and noise reduction strategies.

ECG monitoring data often contains motion artefacts, which are both inevitable and unpredictable. These artefacts have long been a problem in ECG measurements, primarily because their frequency spectrum completely overlaps with the components of the ECG signal, such as the P wave, QRS complex, and T wave. It can be difficult to reduce motion artefacts since doing so runs the risk of obliterating important data from the ECG signal [14]. EMG noise, which is brought on by electrical activity in skeletal muscles and can distort the ECG signal, is another form of interference in ECG signals. One of the numerous potential causes of EMG noise is muscle contractions [15]. The P wave, QRS complex, and T wave, the three main parts of the ECG waveform, may become distorted because of this noise. It could be challenging to recognize and interpret the ECG signal appropriately because of the changing structure of these ECG complexes. The Einthoven's Triangle technique is one way to lessen the effect of EMG noise on the ECG signal. This method improves the quality of the ECG signal by reducing the impact of EMG disturbances for more accurate analysis and diagnosis. Figure 1 displays the corrupted ECG signal affected by motion artefacts and EMG noise, along with the altered ECG waveform resulting from these interferences. Researchers and healthcare professionals continually strive to develop advanced signal processing techniques and noise reduction algorithms to enhance the reliability and fidelity of ECG monitoring data, ensuring the accuracy of medical assessments, and improving patient care.

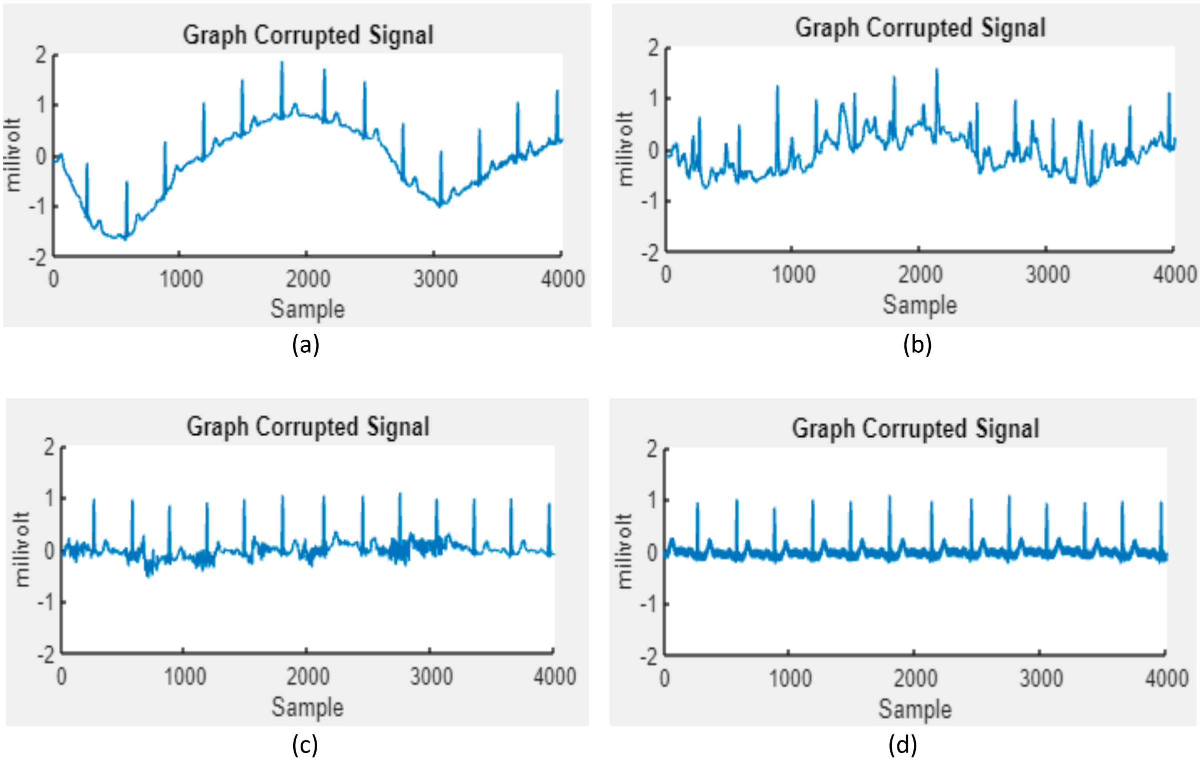

Fig. 1. ECG contaminates with noises (a) BW (b) EMG (c) MA (d) PLI

A particular kind of self-adjusting digital filter known as an adaptive filter has the capacity to automatically update its filter coefficients in response to variations in the input signal. An adaptive algorithm is used to enable the filter to continuously alter its settings in response to the characteristics of the incoming signal, enabling this adaptability. There are several applications for adaptive filters in current digital signal processing (DSP) hardware. One of the main uses of adaptive filters is noise cancellation, which involves removing unwanted noise from a signal to raise its quality and boost the accuracy of future studies or measurements. The use of adaptive filters is also crucial in improving biological signals. They can improve the accuracy of biomedical signals, such as ECG or EEG, by lowering interference and artefacts, allowing for improved patient monitoring and diagnosis. Additionally, active noise control (ANC) systems use adaptive filters.

In noise-cancelling headphones or other ANC devices, the adaptive filter works to reduce background noise to give the user a quieter environment. Adaptive filters are also crucial parts of adaptive control systems, where they aid in modifying and optimising control parameters based on real-time feedback, assuring a dynamic and responsive control mechanism for a variety of applications. Adaptive filters are, in general, vital instruments for digital signal processing due to their adaptability and versatility. They have a substantial impact on noise reduction, signal amplification, and control systems in a variety of industries, including biomedical engineering, audio technology, and more taken from [16,17].

An adaptive filter of length L that takes as input a sequence of x(n) and whose weights vary according to:

$$w(n+1) = w(n) + \mu\, x(n)e(n) \tag{1}$$

The desired signal, d(n), is created by applying the adaptive filter depicted in Figure 2 to a signal, s(n), that has been polluted with a noise signal. Filtering error is displayed as:

$$s(n) = x(n) - d(n) \tag{2}$$

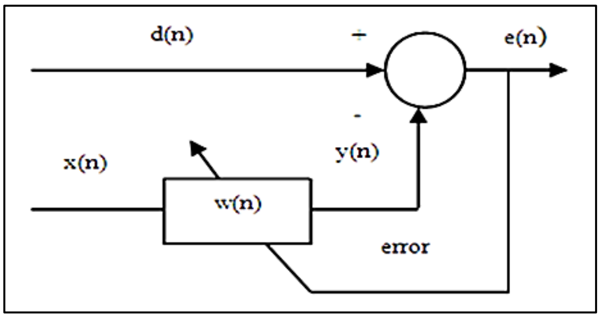

Fig. 2. Adaptive filter structure

When compared with the conventional LMS adaptive filter, the normalising step size parameter of the normalised LMS (NLMS) approach improves both the degree of stability and the pace of convergence of the filter output [18]. The NLMS algorithm's weight update is provided by:

$$w(n+1) = w(n) + \frac{\mu\, x(n)e(n)}{x^T(n)x(n)} \tag{3}$$

where μ is a predetermined convergence factor that is used to control maladjustment and $x^T(n)x(n)$ is the input signal that has been normalized.

Compared to the normalised least mean squares (NLMS) algorithm, the proportionate normalised least-mean-square (PNLMS) approach can converge more quickly [19]. In this specific case, at each tap position, the gain has been adjusted to the filter. The gain is roughly proportionate to the tap weight at each position. The additional step-size update $G(n+1)$'s PNLMS algorithm for the weight is as follows:

$$w(n+1) = w(n) + \frac{\mu\, x(n)e(n)G(n+1)}{x^T G(n+1)x(n)} \tag{4}$$

where the gain diagonal matrix is:

$$G(n+1) = diag[g_1(n+1), \cdots + g_L(n+1)] \tag{5}$$

The gain is approximated as,

$$g_l(n+1) = \frac{\gamma_l(n+1)}{\frac{1}{L}\sum_{i+1}^{L}\gamma_l(n+1)}, with\ l = 1, \dots, L \tag{6}$$

with the current impulse response as,

$$\gamma_l(n+1) = max[\gamma_{min}(n+1), |\widehat{w}_l(n)|], \text{ and} \tag{7}$$

$$\gamma_{min}(n+1) = \rho\, max\left[\delta_p, |\widehat{w}_1(n)|, |\cdots|, |\widehat{w}_L(n)|\right] \tag{8}$$

where the variables ρ and δ_p typically have values of 5/L and 0.01 respectively. To prevent overflow, the small positive number δ_p is employed. Now that all coefficients are zero (at the beginning), the constant ρ is essential, along with, to prevent the very small coefficient from being extinct. When ρ and δ_p are too large, the initial convergence becomes slow.

When the current impulse response is dispersed, the PNLMS algorithm performs worse than the NLMS algorithm. To address the shortcomings of the original PNLMS algorithm, an improved version was developed (IPNLMS) taken from [20]. Combining proportionate (PNLMS) and non-proportionate (NLMS) updating techniques is what the IPNLMS algorithm does. The diagonal matrix and weight update algorithm that are associated to IPNLMS are the same as those in Eq. (4) and Eq. (5), respectively. But according to [12], the anticipated benefit with IPNLMS is:

$$g_l(n+1) = \frac{1-\alpha}{2L} + (1+\alpha)\frac{|w_l(n)|}{2\left|\sum_l^0 w_l(n)\right|}, \;\; l = 0,1,\dots,L-1 \tag{9}$$

α factor of controls the update algorithm. It should be noticed that the second component in Eq. (9) becomes zero when $\alpha = -1$ and operates as a typical NLMS algorithm as a result. Even though for is unity, the first term in Eq. (9) goes to zero, causing it to behave as PNLMS.

A supplementary μ-law to PNLMS (MPNLMS) method is used in their study proposal to overwhelm the delayed convergence during PNLMS, and it produces improved results than the PNLMS algorithm taken from [21]. In this case, easing PNLMS's computational burden may help to lessen the algorithm's intrinsic computational complexity and improve converge performance. The weight and diagonal matrices are updated by MPNLMS using the same process as Eq. (4) and Eq. (5), respectively. The PNLMS algorithm now features a μ-law with,

$$F(|\widehat{w}_l(n)|) = \frac{\ln(1+\alpha|\widehat{w}_l(n)|)}{\ln(1+\alpha)}, |\widehat{w}_l(n)| \ll 1, l = 1,\dots,L; \;\; \alpha = \frac{1}{\varepsilon} \tag{10}$$

and modify the existing impulse response of PNLMS in Eq. (8) to,

$$\gamma_{min}(n+1) = \rho\, max\left[\delta_p, F|\widehat{w}_1(n)|, |\cdots|, F|\widehat{w}_L(n)|\right]$$

and an estimate of the gain can be derived from Eq. (9). The purpose of the constant 1 in equation in (10) is to prevent a negative infinity from occurring at the beginning of the process when $w(n+1) = 0$. The denominator $\ln(1+\alpha)$ normalizes the $F(|\widehat{w}_l(n)|)$ to be in the range of 0 to 1. The value of the variable ε is a modestly positive number that is determined by the amount of EMG noise. The Signal-to-Noise Ratio (SNR) of each signal is used to determine which value should be used.

Recursive Least Squares (RLS) is an adaptive algorithm used in the field of signal processing and system identification. It is particularly useful for estimating the parameters of a linear model in real-time as new data points become available. RLS is commonly used for tasks such as adaptive filtering, channel equalization, noise cancellation, and system modelling. The main idea behind the RLS algorithm is to update the parameter estimates iteratively as new data is acquired. It uses a recursive formulation to efficiently compute the updated parameter estimates based on the current data point and the previously estimated parameters. This makes RLS well-suited for applications where data arrives sequentially and needs to be processed in real-time. Initialize the estimate error covariance matrix P and a forgetting factor λ, $(0 < \lambda \leq 1)$, which determines the influence of past data on the estimates. The new input vector $x(t)$ received corresponded to the output $y(t)$, the Kalman gain $K(t)$ is computed based the following Eq. (12):

$$K(t) = \frac{P(t-1)*x(t)}{(\lambda+x(t)'*(P(t-1)*x(t)} \quad (12)$$

and updated the estimate error covariance matrix P with

$$P(t) = \frac{1}{\lambda} * [P(t-1) - K(t) * x(t)' * P(t-1)] \quad (13)$$

In summary, LMS is simpler, computationally less intensive, and suitable for scenarios where computational resources are limited and convergence speed is not a critical factor. RLS, on the other hand, is more computationally intensive but provides faster convergence and is better suited for applications with rapidly changing parameters or highly correlated data. However, the research aimed to reduce the noises in ECG signal for further process to be taken from. The clean ECG signal needs to be as clean as they can to ensure the right output is given.

Discrete wavelets transform (DWT) is a popular wavelet transform function for denoising ECG data. In numerical analysis and functional analysis, the term "DWT" refers to any wavelet transform in which the wavelets are discreetly sampled. It stores information for both frequency and position, which gives it a major advantage over the Fourier transform and other wavelet transforms in terms of temporal resolution. The wavelet analysis method employs a mother wavelet prototype function. As seen in Figure 3, the prototype wavelet is employed for frequency analysis with a dilated, low-frequency version being used for temporal analysis.

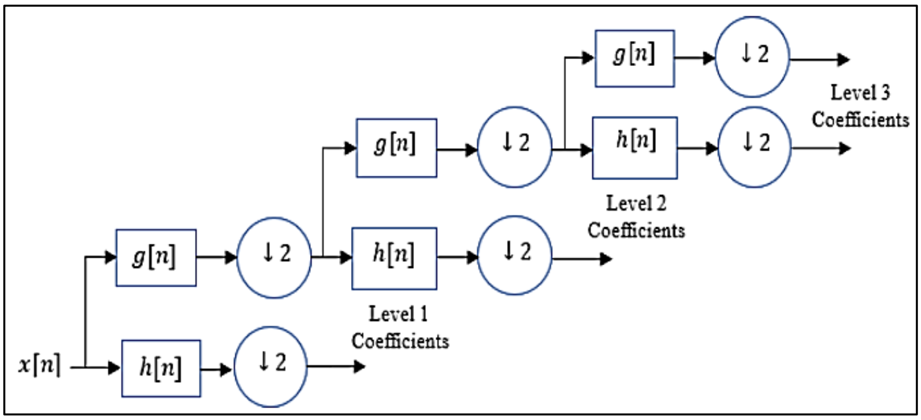

Fig. 3. Wavelet Transform structure

A high pass filter is used to concurrently breakdown the signal. The outputs provide the approximation and detail coefficients (from the low pass filter) for the high pass filter. It's important to understand how the two filters interact. However, because half of the signal frequencies have been removed, half of the samples may now be disregarded. Mallat's and the common notation are then used to subsample the filter output by 2, where $g[n]$ stands for a high-pass filter and $h[n]$ for a low-pass filter,

$$y_{low}[n] = \sum_{k=0}^{n} \binom{n}{k} x^k a^{n-k} x[k]h[n-k], \text{ and} \quad (14)$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \tag{15}$$

Since only half of each filter output feature is included in the signal, this decomposition has reduced the time resolution by half. However, with the subsampling operator, each output has a frequency band that is half that of the input, doubling the frequency resolution.

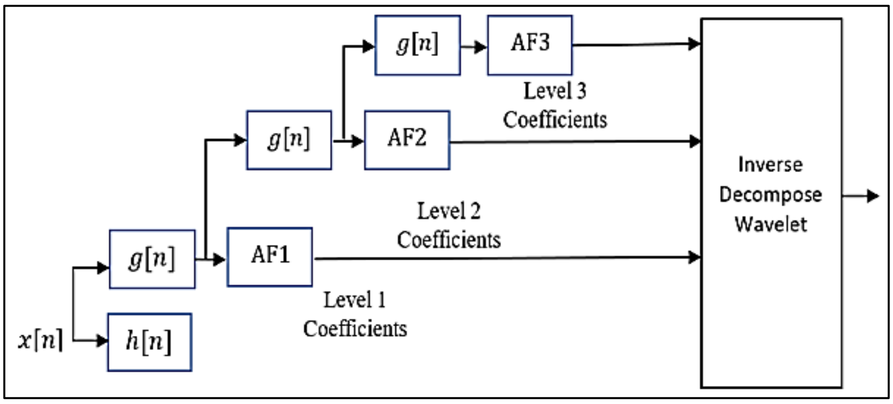

Fig. 4. Combination of wavelet transform and adaptive filter structure

In the beginning of the process involving the combination of WT and AF, the noisy signal will be decomposed by WT into high-pass and low-pass filters. The high-pass filter is indicated by the notation g[n], while the low-pass filter will be indicated by the notation h[n]. Following that, the output h[n] will be fed into AF as the input, where it will be filtered. Depending on the preferences of the user, this procedure will continue to repeat itself across several levels. Through a process known as the inverse decomposition wavelet, the output of the AF at each level will be combined to produce a complete signal.

3. Results

Using wavelet transform (WT) based filter, adaptive filter (AF) based filter, and the combinations of AF-WT based filters are recommended for the elimination process, the interference of main noises (BW, PLI, MA, and EMG) in ECG signal. The designed simulation is created and applied to the distorted ECG data using MATLAB simulation software. Both AF and WT based filters have their pro and con according to the research. AF-based filters may effectively decrease uncorrelated noise since they have the signal as a reference. However, since the spectrum of the AF-based filter totally overlapping the ECG signal, it was unable to filter the correlated noise. Therefore, WT-based filters are used to lessen the amount of noise affecting the ECG signal. The literature also states that WT-based filters may decrease high frequency sound, whereas AF-based filters are effective for reducing low frequency signal. The results below demonstrate the filters' capacity to slash unnecessary ECG signal signals.

The Sqtwolog, Rigrsure, Heursure, and Minimax were employed in the study as the thresholding techniques for the WT-based filter. On the other hand, recursive least square (RLS), least mean square (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) were used in the AF based filter, respectively. In comparing the effectiveness of each of these methods then Signal to Noise Ratio (SNR) measurement are assessed. The combination of AF-WT based filters is applied to measure the capability bot filter to remove low and high frequency noises simultaneously.

Electromyogram (EMG) noise can appear because of electrode placement on various body parts. Because each electrode is in a different area of the body, the EMG noise around each electrode is distinct and uncorrelated. Skin effect noise is another name for EMG noise is taken from [15]. Motion artefact (MA) noise is the most difficult to get rid-off of all the many types of noise. The spectrum of this noise, which results from patient movement, coincides with that of the actual ECG signal. A different readout from the MA noise results from each movement the patient makes, taken from [14]. Most ECG measurements are normally collected when the patient is at rest and free from MA noise, even if continuous ECG monitoring during activities like jogging may catch the MA noise. Table 1 is used by researchers to examine how well different filters remove BW, PLI, EMG, and MA disturbances from ECG signals. For precise diagnosis and monitoring, noise from ECG data must be effectively reduced [22]. Figure 5 shows the PLNMS wavelet adaptive filter performance.

According to the results in Table 1, the PNLMS adaptive filter performs the best at reducing baseline wander (BW) noise from the ECG signal, obtaining a remarkable Signal to Noise Ratio (SNR) value of 29.01. The MPNLMS adaptive filter comes in second with a SNR of 19.41, then NLMS comes in third with a SNR of 19.27, and IPNLMS comes in third with a SNR of 10.37. However, the standard LMS adaptive filter falls short of the competition, with a lower SNR value of only 5.76. RLS can perform 13.84 of SNR value. The PNLMS adaptive filter displaying greater performance in removing BW noise from the ECG data, the large difference in SNR values across the adaptive filters emphasises the significance of choosing the best denoising technique. Achieving a remarkable Signal to Noise Ratio (SNR) value of 39.60, the adaptive filter utilising the normalised least mean square (NLMS) algorithm exhibits the best performance in removing powerline interference (PLI) from the ECG signal based on the results shown in Table 1. With a SNR of 37.01, the proportional normalised least mean square (PNLMS) and improved proportionate normalised least mean square (IPNLMS) adaptive filters follow closely, both of which exhibit comparable efficacy in reducing PLI. With SNR values of 38.88 and 39.15, respectively, the micro proportional normalised least mean square (MPNLMS) and conventional LMS adaptive filters also perform well in PLI elimination. The RLS adaptive filter performs better than others with 35.89 on SNR. Each filter's SNR values show how well it can reduce PLI interference from the ECG signal.

Table 1
ECG wavelet adaptive filtering performance

Adaptive filter type	SNR, dB			
	BW filtering	PLI eliminating	EMG removing	MA reducing
LMS	5.76	39.15	5.76	21.67
NLMS	19.27	39.60	9.85	22.46
PNLMS	29.01	37.01	10.37	25.31
IPNLMS	10.37	37.01	10.37	25.31
MPNLMS	19.41	38.88	5.12	23.87
RLS	13.84	35.89	16.57	18.76

The RLS adaptive filter outperforms other filters with 16.57 of SNR, show the highest performance in removing the electromyogram (EMG) effect from the ECG signal, according to the results in Table 1. The proportional normalised least mean square (PNLMS) and improved proportionate normalised least mean square (IPNLMS) adaptive filters, both of which have an SNR of 10.37. Following closely behind, the NLMS adaptive filter accomplishes EMG removal with an SNR of 9.85. With a SNR of 5.76, the conventional LMS adaptive filter falls short and shows less efficiency for EMG noise reduction. With an SNR of only 5.12, the micro proportional normalised least mean square (MPNLMS) adaptive filter performs poorly in removing EMG. Both the proportional normalised least mean square (PNLMS) and improved proportionate normalised least mean square (IPNLMS) adaptive filters demonstrate remarkable performance in the most recent analysis for motion artefact (MA) noise removal, attaining an SNR of 25.31. With a SNR of 23.87, the micro proportional normalised least mean square (MPNLMS) adaptive filter comes in second place and shows good MA noise reduction performance. While the conventional LMS adaptive filter performs substantially lower with a SNR of 21.67, the normalised least mean square (NLMS) adaptive filter performs decently with a SNR of 22.46. The RLS on can reduce up to 18.76 on SNR for MA noise.

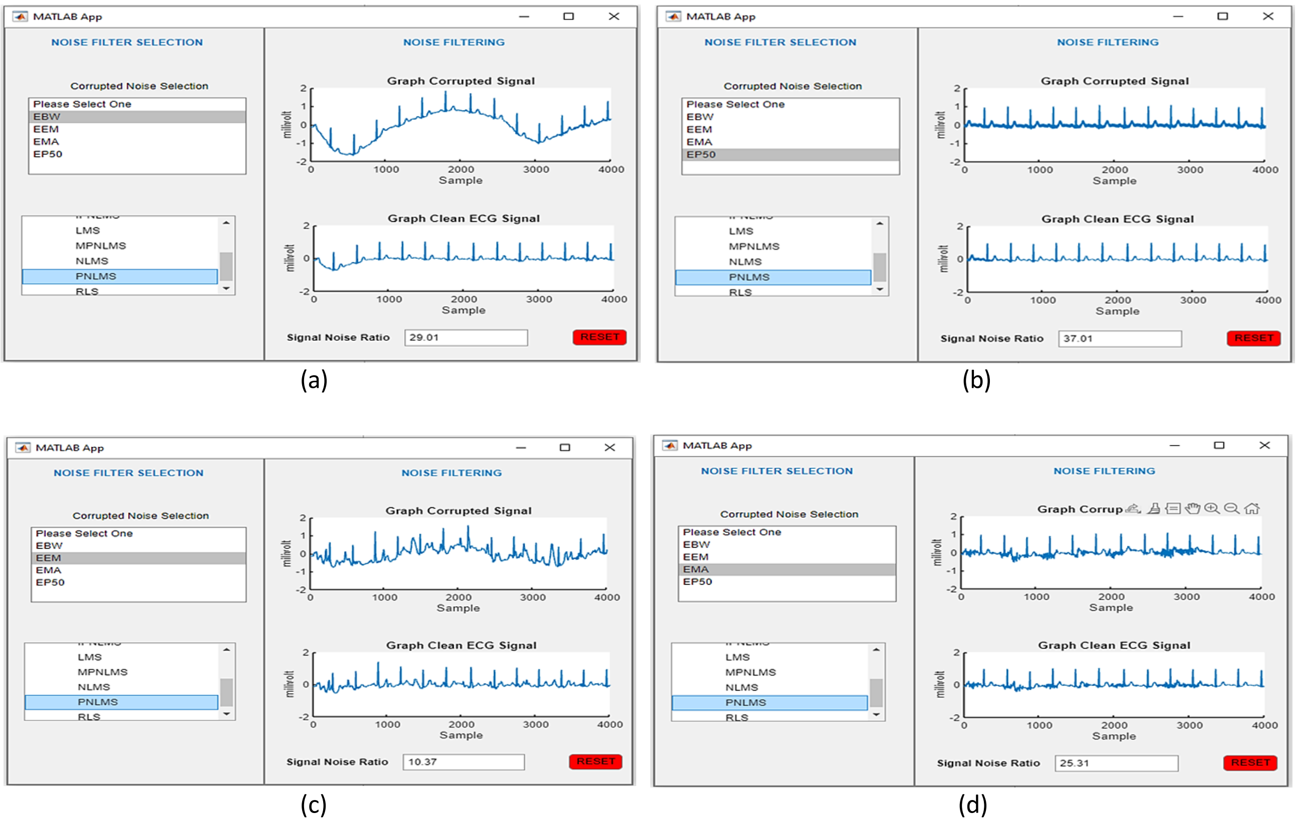

Fig. 5. PLNMS wavelet adaptive filter performance (a) BW filtering (b) PLI eliminating (c) EMG removing (d) MA reducing

The most effective denoising technique for noise types in ECG signals can be found with the aid of this research, which is significant for researchers. People can collect high-quality ECG signal by using modern denoising techniques like PNLSM, which leads to more precise diagnosis and better patient care. It can benefit from the comparison's findings because they can use them to identify the best denoising methods for dealing with powerline interference in ECG data. The NLMS adaptive filter, which has the greatest SNR value among the investigated filters, emerges as the best performer for PLI eradication. However, depending on specific application needs and computational considerations, the other adaptive filters, such as RLS, PNLMS, IPNLMS, MPNLMS, and LMS, also exhibit comparable performance and provide workable solutions for PLI reduction in ECG signals. The results show that the EMG noise can be effectively removed from the ECG signal using both the PNLMS and IPNLMS adaptive filters. The standard LMS and MPNLMS filters, on the other hand, only partially succeed in eliminating EMGs, whereas the NLMS adaptive filter does rather well.

Overall, these results show how effective adaptive filters like PNLMS and IPNLMS are at removing MA noise from ECG signals. Another effective choice for this task is the MPNLMS adaptive filter. These cutting-edge denoising approaches can be used by researchers to improve the quality and accuracy of ECG data, enabling more precise diagnoses and better patient care in situations when MA noise is a significant role. Table 1 shows the difference between the best technique to reduce the stationary and non-stationary noise signal. From the table, it shows RLS is good for stationary noise signal, but other filters (except LMS) capable to reduce noise effect both, for stationary and non-stationary.

The proportionate normalised least mean square (PNLMS) adaptive filter stands out as the best option based on the thorough analysis of the adaptive filters' performance for baseline wander (BW), powerline interference (PLI), electromyogram (EMG), and motion artefact (MA) noise removal. The PNLMS filter is a dependable alternative for denoising ECG signals since it consistently achieves excellent SNR values for all types of noise removal. A decent SNR reading for literature often falls between 20 and 30 on SNR. Table 1 amplifies the PNLMS filter's usefulness in noise reduction for several noise types in ECG signals by amplifying the fact that it is the only tested filter to fall within this required range. The results lend credence to the idea that the PNLMS adaptive filter is the best option for denoising ECG signals due to its superior performance and compliance with accepted standards for excellent SNR readings. Researchers can acquire high-quality and trustworthy ECG signals by using the PNLMS filter in the processing of ECG data, leading to more accurate diagnoses and better patient care. The PNLMS adaptive filter shows itself to be a highly successful solution in this regard. Choosing the right denoising technique is essential for optimising the signal quality and efficacy of ECG signal processing.

4. Conclusions

To obtain a free-noise ECG signal, a good denoising technique must be implemented. On the other hand, major noise contaminating in ECG signal such as baseline wander (BW); powerline interference (PLI); motion artefact (MA); and electromyogram (EMG) effects need to be reduced from ECG signal need to be removed. In the research, wavelet transform (WT) based filter, adaptive filter (AF) based filter, and the combinations of AF-WT based filters are suggested for the eliminating process. The MATLAB simulation software successfully designed WT, AF and AF-WT based filters. From the results, it can be concluding that AF and WT based filter have their own limitation which AF based filter is better for low frequency removal while WT based filter is good high frequency elimination. The combination of both based filters shows the better performance on removing low and high frequency noise simultaneously. Some recommendations on WT, various types of mother wavelet can be explored since the research only concentrating on Daubechies mother wavelet. On top of that, only RLS and LMS based adaptive filter are used in this work and number of AF based filter can be suited for future works.

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