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Comparison on LMS Adaptive Filter Performance in Denoising ECG Signal

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ABSTRACT

Since heart failure became a pressing issue, the development of the electrocardiogram (ECG) signal denoising technique has accelerated. Since heart failure issues might result in mortality, researchers have developed a good method for lessening the impact of noise in the ECG signal to avoid incorrect diagnoses and unnecessary operations. A precise denoising approach must be used to produce a free-noise ECG signal. The ECG signal needs to be cleaned up from major noises, such as baseline wander (BW), powerline interference (PLI), motion artefact (MA), and electromyogram (EMG). In the study, filters based on adaptive filters (AF) are recommended for the filtering stage. The design of the AF and the comparison performance displayed in the signal to noise ratio (SNR) test will be done using MATLAB simulation software. The results demonstrate that the proportionate normalise least mean square (PNLMS) adaptive filter performs better than other adaptive filters. The PNMLS adaptive filter reduces the BW, PLI, EMG, and MA noise effects by, respectively, 13.72 dB, 35.27 dB, 11.54 dB, and 75.41 dB.

Keywords:

Electrocardiogram; Adaptive filter; Signal to noise ratio

1. Introduction

The analysis of 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 [1-3]. 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 makes it difficult to interpret correctly is referred to as interference. The ECG signal may contain a few types of interference, including BW [4], PLI [5], MA [6], and EMG [7].

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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 about by electrical activity in skeletal muscles that may cross over with the ECG signal. The MA noise, on the other hand, 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 filtering was used in several applications for noise cancellation. Kose *et al.,* used adaptive filter-based least mean square (LMS) and recursive least square (RLS) to remove EMG noise [8]. For noise cancellation, adaptive filtering is frequently used in a variety of applications. Kose *et al.,* work specifically targeted electromyogram (EMG) noise removal and used the recursive least square (RLS) and adaptive filter-based LMS adaptive filtering techniques [8]. 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. The performance of these filters is compared using the fidelity parameters mean square error (MSE), normalized root mean squared error (NRMSE), SNR, percentage root mean squared difference (PRD), and maximum error (ME). In the ECG signal, BW and PLI are two common types of noise. Researchers employ several fidelity measures to assess the efficacy of the adaptive filtering techniques outlined before. The MSE, NRMSE, SNR, PRD, and 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 LMS approach and an adaptive filter, on the other hand, were used by Shaddeli *et al.,* to diminish the BW and PLI effects in the ECG signal [9]. 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.,* the emphasis was on utilizing adaptive filtering in conjunction with the LMS method to reduce the effects of BW and PLI in the ECG signal [9]. The researchers combined the performance of adaptive filtering with two cutting-edge methods: the GA and 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.,* 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 [10]. 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 & Kokate [11], their goal was to use multichannel ECG leads to differentiate between fetal ECG signals during pregnancy and labour. 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 foetus 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 analysed 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.

LMS adaptive filter is seen to be able to filter noise within a short period. However, the ability of the LMS adaptive filter is only for stationary signals and unable to provide good performance for the non-stationary signals. Several modified approaches to the LMS adaptive filter have been made in echo cancellation and double talk remover applications. Those applications will be used to reduce the effect of noise in the ECG signal.

2. Methodology

The major interferences that significantly affect the contamination of ECG signals are BW, PLI, MA and EMG [12]. 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 [12]. 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 [13]. 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 [14]. 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. Prominent sources of noise in ECG readings include baseline wander, powerline interference, motion artefact, and electromyogram interference. 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 [15]. 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 [16]. 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 technique helps reduce the effect of EMG interference and improve the quality of the ECG signal 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.

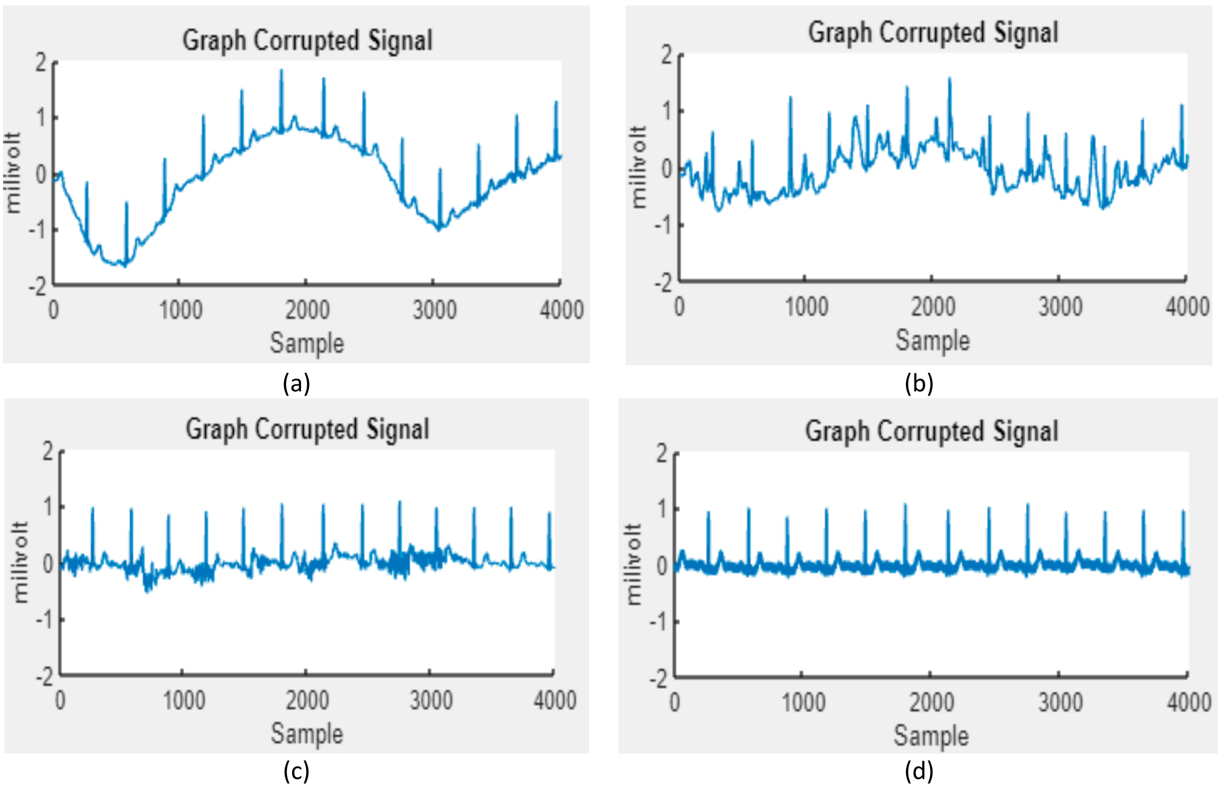


Fig. 1. ECG contaminates with noises; a) BW, b) EMG, c) MA and d) PLI

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. Adaptive filters also play a significant role in the enhancement of biomedical 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 [17,18].

A length L based adaptive filter having an input sequence of $x(n)$ and weights that are changed in accordance with:

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

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

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

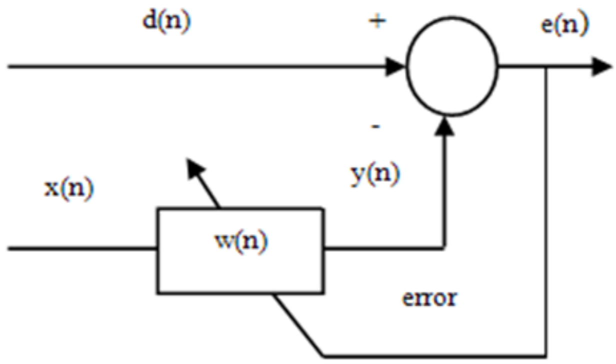


Fig. 2. Adaptive filter structure

When compared to the conventional LMS adaptive filter, the normalising step size parameter of the normalised LMS (NLMS) algorithm improves the stability and convergence rate of the filter output [19]. 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 preset convergence factor to control maladjustment and $x^T(n)x(n)$ is the input normalised signal.

Compared to the normalised least mean squares (NLMS) algorithm, the proportionate normalised least-mean-square (PNLMS) approach can converge more quickly [20]. At each tap position in this instance, 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:

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

and the diagonal matrix of the gain is

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

The gain can be estimated as

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

with the current impulse response as

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

and

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

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) [21]. 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 [13], the anticipated benefit with IPNLMS is

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

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 (9) goes to zero, causing it to behave as PNLMS.

An additional μ-law to PNLMS (MPNLMS) method is used in their study proposal to overcome the delayed convergence during PNLMS, and it produces better results than the PNLMS algorithm [22]. 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

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

and change the current impulse response of PNLMS in Eq. (8) to

$$\gamma_{min}(n+1) = \rho \max\left[\delta_p, F|\hat{w}_1(n)|, |\cdots|, F|\hat{w}_L(n)|\right] \tag{11}$$

and the gain is estimated based on Eq. (9). The constant 1 used in Eq. (10) is to avoid negative infinity at the initial stage when $w(n+1) = 0.$ The denominator $\ln(1+\alpha)$ normalizes the $F(|\hat{w}_l(n)|)$ to be in the range of 0 to 1. The variable ε is a small positive number chosen based on the EMG noise level. The ε is choose based on the Signal to Noise Ratio (SNR) of each signal.

3. Results and Discussions

LMS-based filter and adaptive filter (AF)-based filter are suggested for the removal of the principal noises (baseline wander, powerline interference, motion artefact, and electromyogram) in ECG signals. Using MATLAB simulation software, a simulation is created and applied to distorted ECG data to assess their performance. The NLMS, PNLMS, IPNLMS, and MPNLMS algorithms of the least mean square (LMS) algorithm are used in the AF based filter. The efficiency of each of these techniques in decreasing the interference brought on by the noises is evaluated and compared. The SNR measurement, which quantifies the ratio of the valuable ECG signal to the undesirable noise, is used in the evaluation.

BW is the term used to describe the noise produced by the ECG measurement devices, and its normal frequency range is 0 to 0.5 Hz [13]. Depending on the frequency of the country's power supply, PLI is noise that comes from the power lines and typically has a frequency of roughly 50/60 Hz [14]. Researchers intend to successfully remove these undesired noises from the ECG signals using LMS and AF-based filters, which will increase the accuracy and reliability of the recorded data for medical diagnosis and analysis. The AF-based filter's choice of many LMS algorithm versions enables a thorough evaluation of each one's performance and aids in determining which approach is best for reducing noise in ECG data in various situations and applications.

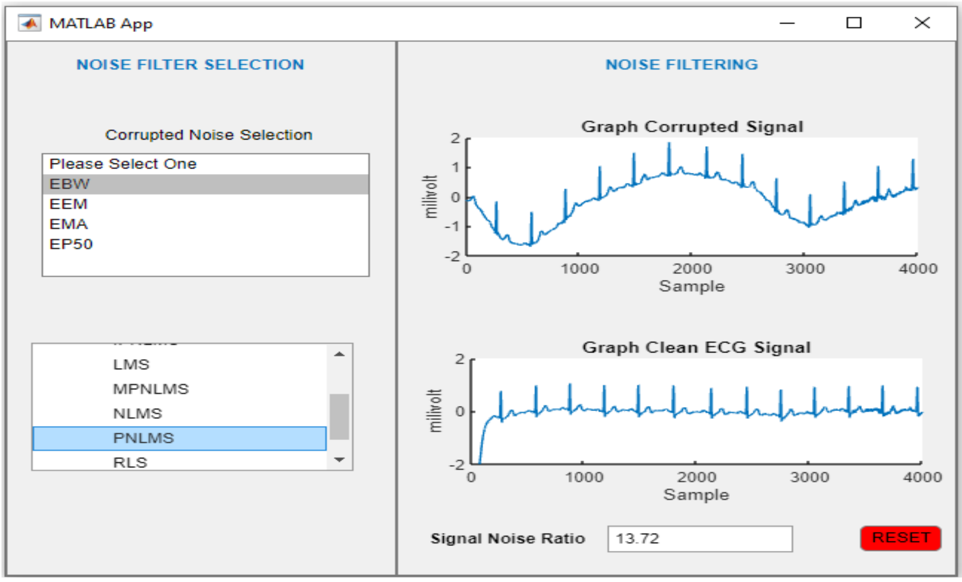
EMG noise can appear because of electrode placement on various body parts. Because each electrode is in a different area of the body, the EMG noise around each electrode is distinct and uncorrelated. Skin effect noise is another name for EMG noise [16]. MA noise is the most difficult to get rid-of of 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 [15]. 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.

Table 1
BW filtering performance

Adaptive filter type	SNR, dB			
	BW filtering	PLI eliminating	EMG removing	MA reducing
LMS	0.47	20.17	5.15	60.71
NLMS	13.72	35.27	11.00	75.83
PNLMS	13.72	35.26	11.54	75.41
IPNLMS	13.72	35.27	11.20	75.04
MPNLMS	13.72	35.27	11.21	75.95

According to the results in Table 1 and Figure 3, all the adaptive filters (except LMS) perform the best at reducing BW noise from the ECG signal, obtaining a remarkable SNR value of 13.72. However, the standard LMS adaptive filter falls short of the competition, with a lower SNR value of only 0.47. Again, all adaptive filters display greater performance in removing PLI from the ECG signal based on the results shown in Table 1. With a SNR of 35.27, the filters show the capability to reduce noise effect compared to standard LMS adaptive filter with only 20.17 on SNR. The MPNLMS) and IPNLMS adaptive filters, both of which have an SNR of 11.20, show the highest performance in removing the EMG effect from the ECG signal, according to the results in Table 1. Following closely behind, the NLMS adaptive filter accomplishes EMG removal with an SNR of 11.00. 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 11.54, the

PNLMS adaptive filter performs other filters in removing EMG. Both the PNLMS and MPNLMS adaptive filters demonstrate remarkable performance in the most recent analysis for MA noise removal, attaining an SNR of 75.83 to 75.95. With a SNR of 75.41, the PNLMS adaptive filter comes later and shows good MA noise reduction performance. While the conventional LMS adaptive filter performs substantially lower with a SNR of 60.71, the IPNLMS adaptive filter performs decently with a SNR of 75.04.



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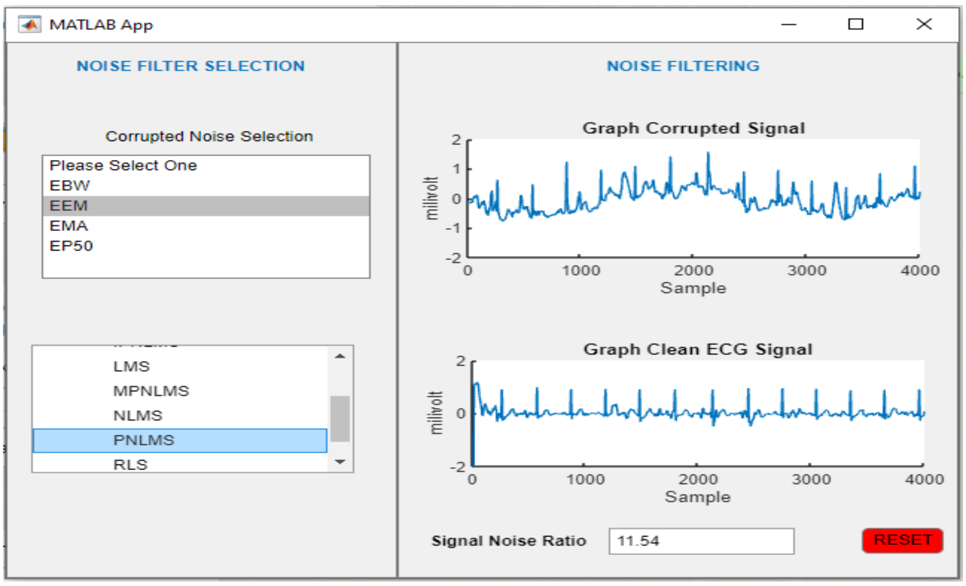

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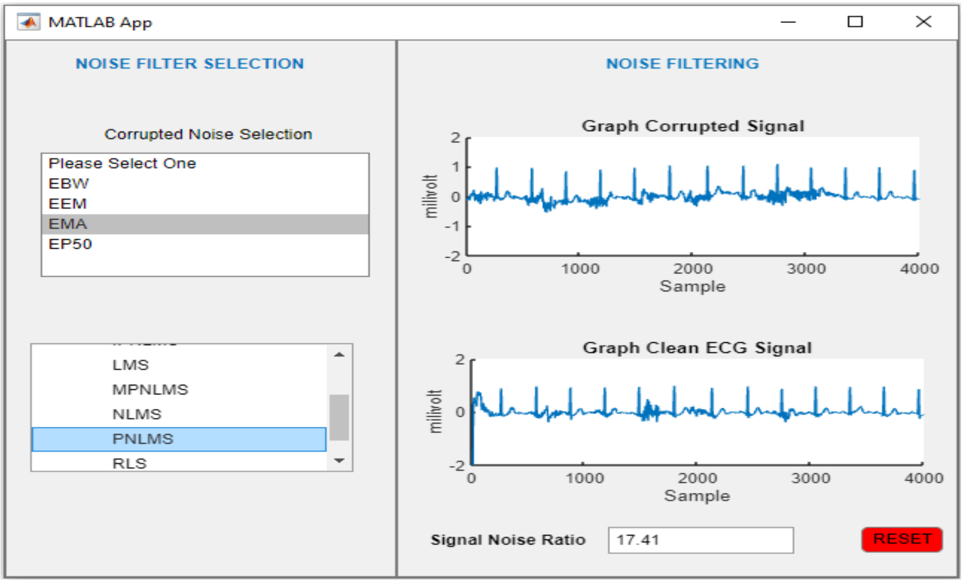

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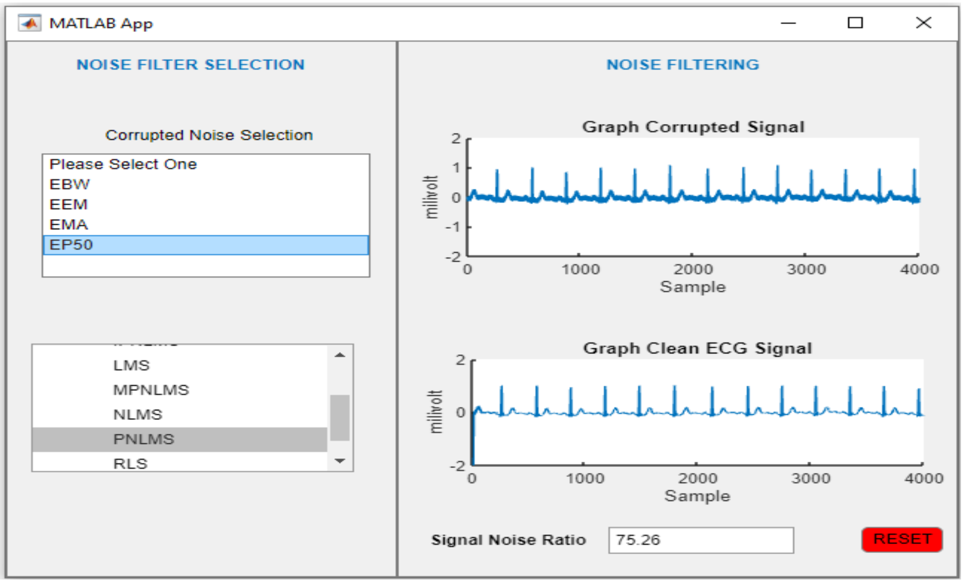

(d)

Fig. 3. PLNMS Adaptive filter performance

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 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.

The PNLMS adaptive filter stands out as the best option based on the thorough analysis of the adaptive filters' performance for BW, PLI, EMG and 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 clean and noise-free ECG signal, a robust denoising technique is essential. The major sources of noise contamination in ECG signals, including BW, PLI, EMG and MA effects, must be effectively reduced or removed. An adaptive-based filter is advised as the preferred noise-elimination technique in this study. Adaptive-based filters were successfully created by the researchers using the simulation software MATLAB. According to the study's findings, the PNLMS adaptive filter performed better than others at reducing the effects of BW, PLI, MA, and EMG sounds. The ECG signal was successfully cleaned of this kind of noise by the PNLMS adaptive filter, producing a clearer and more accurate representation of the underlying ECG data. The researchers were also able to improve the denoising performance by altering the structure of the LMS adaptive filter. These changes helped to reduce noise more effectively and better preserve the key components of the ECG signal. The study's result emphasizes the importance of using adaptive-based filters to reduce noise in ECG readings. According to the study, the PNLMS adaptive filter is particularly good at reducing the effects of BW, PLI, MA, and EMG noise, which results in a higher-quality ECG signal. By optimizing the structure of the LMS adaptive filter, the denoising performance was further enhanced, underscoring the continuous efforts to develop better noise reduction techniques for accurate ECG signal analysis in medical applications.

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