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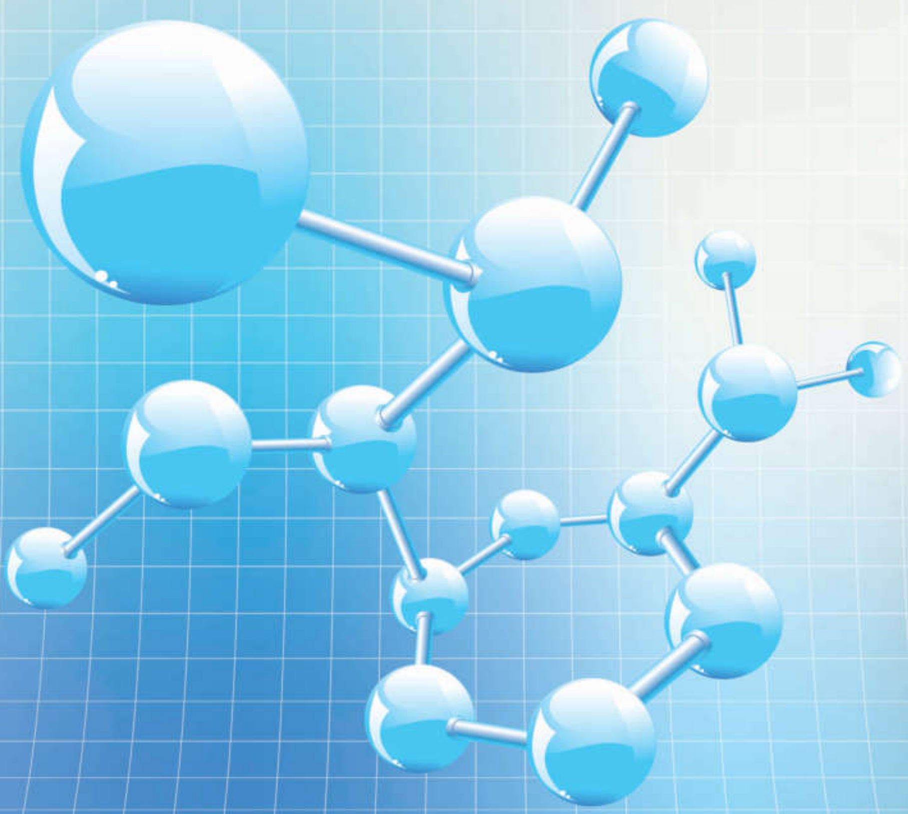

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Điện thoại: (0220) 3587213, Fax: (0220) 3882 921, Hotline: 0912 107858/0936 847980.
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Performance comparison between FIR and LMS filters in noise processing of EEG signals

So sánh hiệu suất giữa bộ lọc FIR và LMS trong xử lý nhiễu tín hiệu điện não đồ EEG

Nguyen Xuan Kien[1*], Bui Phuong Thao[1], Do Van Dinh[2]

**Corresponding author: nxkien@ictu.edu.vn*

[1]University of Information and Communication Technology - Thai Nguyen University

[2]Sao Do University

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Abstract

This paper compares the performance of two electroencephalogram (EEG) signal filtering methods: the Finite Impulse Response (FIR) low-pass filter and the Least Mean Squares (LMS) adaptive filter, in terms of their ability to remove 50 Hz noise while preserving key frequency bands such as Delta, Theta, Alpha, and Beta. The evaluation metrics include the signal-to-noise ratio (SNR), mean squared error (MSE), processing time, harmonic distortion, and phase delay. The results indicate that while both methods significantly reduce noise, the FIR filter outperforms the LMS filter in terms of noise removal and preservation of EEG signals, demonstrating good accuracy in both time and frequency domains. The FIR filtering method proves superior in maintaining EEG signal integrity, while the LMS technique retains advantages in dynamic noisy environments, effectively reducing noise in the low and mid-frequency ranges. This study provides important insights into selecting the appropriate filtering method to enhance signal quality, minimize noise, and improve reliability in EEG analyses.

Keywords: *EEG signal processing; FIR filter; LMS filte; noise reduction; filter performance comparison.*

Tóm tắt

Bài báo này tiến hành so sánh hiệu suất của hai phương pháp lọc tín hiệu điện não đồ (EEG), là bộ lọc thông thấp Phản hồi xung hữu hạn (FIR) và bộ lọc thích nghi bình phương trung bình nhỏ nhất (LMS), trong việc loại bỏ nhiễu 50 Hz mà vẫn giữ nguyên các dải tần số quan trọng như: Delta, Theta, Alpha và Beta. Các chỉ số được đánh giá gồm tỷ lệ tín hiệu trên nhiễu (SNR), lỗi bình phương trung bình (MSE), thời gian xử lý, độ méo hài và độ trễ pha. Kết quả cho thấy, mặc dù cả hai phương pháp đều làm giảm nhiễu đáng kể, nhưng bộ lọc FIR có hiệu suất tốt hơn trong việc loại bỏ nhiễu và bảo toàn các tín hiệu EEG so với bộ lọc LMS, với độ chính xác tốt trong miền thời gian và tần số. Phương pháp lọc FIR tỏ ra vượt trội trong việc bảo toàn tín hiệu EEG, trong khi kỹ thuật lọc LMS vẫn có lợi thế trong các môi trường nhiễu thay đổi, cho hiệu quả về việc giảm nhiễu trong dải tần thấp và trung. Nghiên cứu này cung cấp những hiểu biết quan trọng về việc lựa chọn phương pháp lọc phù hợp, nhằm nâng cao chất lượng tín hiệu, giảm nhiễu và cải thiện độ tin cậy trong các phân tích EEG.

Từ khóa: *Xử lý tín hiệu EEG; bộ lọc FIR; bộ lọc LMS; giảm nhiễu; so sánh hiệu suất bộ lọc.*

1. INTRODUCTION

Electroencephalography (EEG) is a relatively common method used for clinical and research purposes, particularly for assessing the brain's activity. One of the most frequent issues associated with the interpretation of the electroencephalogram (EEG) signals involves noise artifacts or interferences, which may include 50 Hz or 60 Hz power line noise, motion-induced noise, and ambient noises. Such noise could easily mask useful brain signals especially when there is a lack of appropriate filters that can help in preserving the important aspects of the data. Accurate noise removal is crucial, especially when targeting the preservation of EEG signal components in specific frequency bands such as alpha (8-12 Hz), beta (13-30 Hz), theta (4-7 Hz) and delta (0.5-4 Hz) that are commonly analyzed in neuroscientific studies.

The introduction of various techniques has sought to resolve the problem of noise in EEG data. One of the

Reviewers: 1. Prof.Dr. Bui Dang Thanh
2. Dr. Nguyen Van Nam

common solutions available today is Finite Impulse Response (FIR) filters, which are favored for their stability and lack of feedback, making them a popular choice for noise removal in various applications [1] - [3]. FIR filters need not be applied to the signal in its entirety as low pass filters can indeed achieve the cutting of spectra that have unwanted frequencies such as the 50 hertz power line noise. Nonetheless, it has been discovered that the efficacy of FIR filters is restricted because they must rely on high-order FIR filters to obtain the targeted suppression levels which will affect the level of computation needed and the time taken [4], [5].

However, adaptive filtering techniques such as the Least Mean Squares (LMS) algorithm are becoming increasingly popular on account of their capacity to update filter coefficients automatically [6] - [8]. It is noted that LMS filters perform better when the noise environment is non-stationary, which is common in EEG applications since the noise environment can be variable. However, even with this feature, LMS filters are not considered to be robust since their performance is heavily dependent on the selection of learning parameters and the existence of a reliable reference signal [9], [10].

Electroencephalogram (EEG) signals are the bioelectrical manifestations of brain activity, recorded via electrodes affixed to the scalp with very low amplitudes (often only a few microvolts) and characterized by nonlinearity and temporal instability. This renders EEG signals rich in valuable information while simultaneously facing numerous noise challenges, due to external factors such as mechanical interference, environmental noise and other physiological signals. To effectively process EEG signals, two primary filtering techniques are employed: FIR (Finite Impulse Response) filters and LMS (Least Mean Square) filters. FIR filters are distinguished by their absolute stability and the capability for linear-phase design, which preserves the original waveform of the signal while eliminating noise; modern design methods such as window optimization and the Parks-McClellan algorithm have significantly enhanced the efficacy of FIR filtering in separating the characteristic frequency components of EEG signals. Conversely, LMS filters, based on a gradient-based adaptive algorithm, automatically adjust filter coefficients according to the error between the expected and actual signals, thereby enabling real-time noise tracking and removal. Variants of LMS, such as the Normalized LMS (NLMS), have been developed to improve convergence speed and stability in complex, ever-changing signal environments like that of EEG. Integrating information from various sources to broaden the perspective on the nature of EEG and the operational mechanisms of FIR and LMS filters will assist readers in grasping both the theoretical foundations and practical applications of these techniques in EEG signal processing systems, thereby providing a solid basis for subsequent advanced analyses and applications.

The research studies documented in references [1-10] have achieved significant progress in the design and application of EEG signal processing techniques. Specifically, Higashi and Tanaka [1] introduced the DFBCSP method to simultaneously optimize the design of FIR filters and spatial filters, thereby facilitating the extraction of discriminative features for brain-signal-based control tasks. Saini et al. [2] proposed novel distortion measures for each frequency band to assess signal quality following denoising via wavelet analysis, whereas the studies by Principe and Smith [3] and Chen et al. [4] improved FIR filter design to ensure rapid response times and cost effectiveness under biological signal processing conditions. Furthermore, the works of Sravani & Kumari [6], Aguilar-Cruz et al. [7], Chang & Wu [9], and Yuan et al. [10] exploited the adaptive capabilities of the LMS filter, demonstrating benefits such as reduced latency, minimized hardware footprint and effective handling of specific noise types like EOG interference. In addition, Capizzi and Sciuto [5] along with Jadav et al. [8] contributed to the advancement of multidimensional filter design and the exploitation of time–frequency domain characteristics of EEG signals. However, despite each study's distinct contributions, a common limitation remains: no research has comprehensively synthesized and compared the performance of the FIR and LMS techniques in denoising EEG signals. This has resulted in a lack of a clear basis for comparing noise reduction performance, computational requirements, and practical applications of each approach, thereby highlighting the need for further research aimed at establishing a detailed comparative framework among existing EEG signal processing techniques.

Although both techniques have been successfully applied for noise suppression, few attempts have been made to systematically investigate the relative performance of the two methods in relation to the specific tasks in EEG signal processing. This absence of a direct comparison diminishes confidence in the primary performance metrics. Most past studies have concentrated their attention on either FIR or LMS filters separately, thus failing to compare the two filters with respect to their ability to retain the critical EEG frequency bands. In addition, limited work has investigated the complexity, lateness, and noise that remains after modulation for EEG signals, which are all important for practical situations for example in clinical or portable EEG.

This research tries to assist in bridging this chasm by making an extensive comparison of two filtering methodologies: FIR low-pass filter and LMS adaptive filter as far as removing 50 Hz noise from EEG signals is concerned. The objective is to determine how well the filters attenuate the power line noise but, the critical alpha, beta, theta, and delta frequency bands are maintained. In this fashion, we expect to analyze both techniques in average noise reduction, computational efficiency, and signal alteration parameters and put forth the most opportune filter for the application of EEG signal processing.

2. MATERIALS AND METHODS

FIR and LMS algorithms are popular in digital signal processing and have a wide application in different fields. In such cases, FIR filters are more useful while LMS filters are more useful in dynamic situations where noise changes and so does the filter automatically in order to maintain the best possible performance. For applications that demand linear phase filtering, FIR filters are a perfect fit as it is stable and non-recursive in nature. On the other hand, high-order FIR filters require more coefficients to get a cutoff that as sharp while analog effort is still low. LMS algorithm, it can adapt filter coefficients to the characteristics of the input signal and noise. The difficult part is choosing an appropriate step-size that allows convergence without instability.

2.1. FIR (Finite Impulse Response) algorithm

FIR filter is a type of linear filter that can be interpreted as the linear combination of the input signal's previous samples. Spectral analysis or signal processing often includes services like denoising, smoothing, and other tasks using filters like these. In particular, FIRs are low-pass filters that find their use practically in getting rid of high-frequency noise. The FIR Algorithm is described as follows [1] - [5]:

The output signal *y[n]* is determined by a convolution product of the presented input signal *x[n]* and the filter coefficients *h[n]*:

$$y[n] = \sum_{(k=0)}^{(M-1)} h[k] \cdot x[n-k] \tag{1}$$

Where:

+ *x[n]* is input signal at the position of *n* time.

+ *h[k]* are filter coefficients (cutoff frequency and filter parameters provide the design).

+ M is the order of the FIR filter: number of filter taps or coefficients.

+ *y[n]* is the output signal for the nnth moment.

Design the FIR Filter: To keep the cutoff frequency and the filter order according to the design requirements, the filter coefficients *h[k]* should be established. Several approaches may be used for design including the Window method or Parks-McClellan Algorithm depending on the factors that are of concern for the filter (passband ripple, stopband attenuation and others).

Execute the Filtering Operation: A discrete-time input signal *x[n]* is filtered by convolving it with filter coefficients *h[k]* to yield the output signal *y[n]*. This requires carrying out the operations of convolution sums as indicated in the above formula for each sample n.

Output: The high cutoff frequencies will be weakened in the filtered output signal owing to the high frequencies being cut off noise such as 50Hz power line interference.

2.2. LMS (Least Mean Squares) algorithm

Adaptive filtering is carried out in the Least Mean Squares (LMS) algorithm by adjusting the filter coefficients with the aim of reducing the difference between the expected and actual output of the filter. LMS filters are useful in instances where the noise sources have been characterized since they make it possible for the filter to evolve and eliminate noise components within it. The LMS algorithm is described as follows [6-10]:

The LMS algorithm evaluates the filter coefficients *w[k]* based on error *e[n]* which is the difference between the signal *d[n]* and *y[n]*:

$$e[n] = d[n] - y[n] \tag{2}$$

Where:

+ *d[n]* is the reference signal such as the noise free EEG signal with 50Hz filter removal.

+ *y[n]* is similar to the output signal from the controlled adaptive filter.

+ *e[n]* is the time *n* error signal which is the dependent variable that the algorithm aims to resolve.

Application of the gradient method leads to the formula stated below, which updates the filter coefficients *w[k]*:

$$w[k] = w[k-1] + 2\mu \cdot e[n] \cdot x[n-k] \tag{3}$$

Where:

+ Learning rate or step size is denoted by μ for easy understanding. Its value can be computed either experimentally or selected. This value dictates the degree of adaptation, whereas a lower value indicates that the change will be gradual.

+ *x[n-k]* is indicative of input signal samples.

+ *w[k]* the filter's coefficients are calculated using an estimation procedure.

Create a filter using LMS before applying it: In creating the resultant filter coefficients values, *w[k]* for this filter is a real number and we can use zero or a very small number as a set close to the true value. It is more important to choose the learning step which can be denoted as *μ*. Also, the filter's length shows the degree of confidence of an estimate. Compute the LMS filter.

$$y[n]=\sum_{k=0}^{L-1}w[k]\cdot x[n-k] \quad (4)$$

At time nnn the output *y[n]* can be determined by using the following formula where a and f denote the current coefficients of the filter.

d[n], *e[n]* have a frame of reference of *d[n]*, which is aimed essentially at distinguishing various kinds of signals, giving *e[n] = d[n] − y[n].*

Output: With the time it takes to run the LMS algorithm, the filter coefficients *w[k]* are expected to tend to those values that provide minimum error signal. This means that the output signal *y[n]* will become more and more free from noise as it progresses through the LMS process further improving the extraction of the required parts of the signal while eliminating those which are unwarranted.

3. RESULTS AND DISCUSSION

The main problem addressed is to filter synthetic EEG signals [11] contaminated with noise, specifically 50 Hz power line interference, using two different filtering methods: a Finite Impulse Response (FIR) filter and an Adaptive Least Mean Squares (LMS) filter.

The experimental database was constructed based on a synthesized EEG signal that simulates the characteristics of actual biological frequency bands. Specifically, the signal was generated over a period of 2 seconds with a sampling rate of 1000 Hz, wherein the primary components include the Delta wave (0.5-4 Hz) with a component at 2 Hz, the Theta wave (4-7 Hz) with a component at 6 Hz, the Alpha wave (8-12 Hz) with a component at 10 Hz, and the Beta wave (13-30 Hz) with a component at 20 Hz, combined with different amplitudes (0.5, 0.3, 0.8, and 0.4 respectively) to replicate the electrophysiological activities of the brain. Additionally, to enhance realism, a small random noise component (scaled to 0.1 times a random value) was added, along with power line interference (50 Hz, amplitude 0.5) - a common noise source in real EEG recording systems. This database structure not only fully simulates the frequency characteristics of brain signals but also enables the evaluation of filtering algorithms (FIR and LMS) under complex noise conditions. Consequently, the experimental system is designed for multidimensional analysis, ranging from processing time, phase delay, and stability to nonlinear distortion metrics and signal energy preservation, thereby providing a solid foundation for comparing the effectiveness of the two filtering techniques in denoising EEG signals.

The goal is to enhance the signal quality by reducing the noise while preserving the characteristics of the original EEG signal, which includes various brainwave frequency bands. Problem requirements:

- The primary task is to remove 50 Hz power line noise from the EEG signal, which interferes with signal interpretation.

- The filtering process should retain important frequency components of the EEG signal (e.g., Delta, Theta, Alpha, Beta bands).

- Performance comparison and evaluation of each filter in terms of Signal-To-Noise ratio (SNR), mean squared error (MSE), frequency band preservation, computational efficiency, processing time, phase delay and harmonic distortion.

Implement the two algorithms FIR and LMS in Matlab according to the following process:

Input:

- A synthetic EEG signal is created, including Delta, Theta, Alpha, and Beta wave components.

- 50 Hz power line noise is added to simulate real-world EEG signal contamination.

- Set initial parameters for FIR and LMS filters.

Step 1: Generate a synthetic EEG Signal with frequency components in specific bands (Delta, Theta, Alpha, Beta). The signal also includes random noise with an SNR is 6.68 dB to simulate real-world variations.

Step 2: 50 Hz sinusoidal noise is added to the generated EEG signal to simulate power line interference.

Step 3: A low-pass FIR filter with a cutoff frequency of 45 Hz is designed to remove the 50 Hz noise.

Step 4: An LMS adaptive filter is initialized concerning the 50 Hz sinusoidal noise. The adaptive filter iteratively updates its coefficients based on the input signal and reference noise, removing the noise component from the signal.

Step 5: The filtered signals are plotted against the original and noisy signals in the time and frequency domains. Power spectral density (PSD) is used to analyze how well each method preserves the signal and removes noise.

Step 6: Performance Evaluation.

- SNR and MSE are calculated to compare the filtering performance of FIR and LMS filters.

- Analysis of computational efficiency (processing time), phase delay and harmonic distortion, each filter's preservation of EEG frequency bands.

Output:

- The outputs of the FIR-filtered and LMS-filtered EEG signals.

-The performance of each filter is evaluated based on:

+ Signal-to-Noise Ratio (SNR): Measures how much the filtering improves the signal clarity.

+ Mean Squared Error (MSE): Quantifies the deviation between the filtered signal and the original signal.

+ Processing time by each filter is measured.

+ The percentage of preserved power in each EEG frequency band (Delta, Theta, Alpha, Beta).

After programming on Matlab according to this implementation algorithm, we obtain the Data Graphs as Figure 1, Figure 2 and the results of filtering performance of FIR and LMS as shown in Table 1.

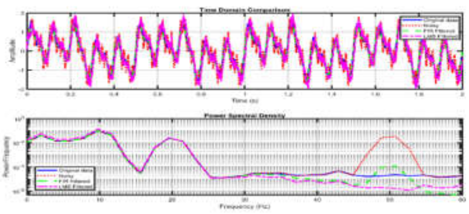

Figure 1. *Time-Domain signal comparison before and after filtering*

The plot in Figure 1 compares the original signal, the noisy signal, and the signals after FIR and LMS filtering in the time domain. We observe that the original data (blue line) is heavily affected by noisy signal (red line) and no longer retains the original waveform. After FIR filtering (green line), the signal is significantly improved, closely restoring the original waveform. LMS filtering (purple line) also improves the signal but is less effective than FIR filtering, with some parts not matching the original signal exactly. Therefore, FIR filtering is more effective at noise removal in the time domain, providing a more accurate restoration of the original signal compared to LMS filtering.

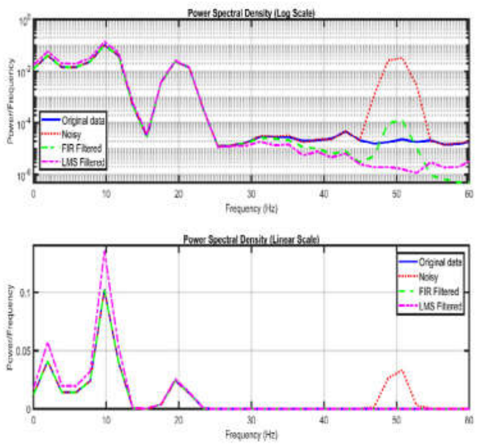

Figure 2. *Frequency response of FIR and LMS filters*

The Power Spectral Density (PSD) plot on both log and linear scales in Figure 2 shows the energy distribution of the signal across different frequency bands. We observe that the noisy signal (red line) has a prominent noise peak around 50 Hz, clearly visible in both plots. After passing through FIR and LMS filters, this noise peak is either eliminated or significantly reduced, restoring the PSD closer to the original signal's spectrum. On the log scale, the FIR (green line) and LMS (purple line) filters both closely resemble the original signal (blue line), but FIR is more accurate. Both FIR and LMS filters effectively reduce high-frequency noise (50 Hz), but FIR provides better accuracy across lower and mid-frequency bands.

Table 1 summarizes key performance metrics comparing FIR and LMS filtering methods, including SNR, MSE, power preservation across frequency bands, processing time, phase delay, stability, and energy preservation.

From Table 1, we have the following observations:

- SNR after FIR filtering is 17.66 dB, significantly higher than the SNR after LMS filtering is 9.72 dB, meaning the signal after filtering by FIR is much cleaner compared to LMS.

- The MSE for FIR filtering is 0.009978, much lower than the MSE for LMS is 0.062113, indicating a better ability to reproduce the original signal of FIR compared to LMS.

- In the Delta, Theta, Alpha, and Beta frequency bands, the FIR filter preserves power very well (close to 100%), while the LMS filter tends to LMS tends to over-amplify power (up to 140.8% in the Delta band), potentially distorting the signal in those bands.

- FIR filter processing time is 0.0721 seconds, much longer than LMS processing time is 0.0046 seconds, which is crucial in real-time applications.

- The stability index of FIR is 19.2747, significantly higher than the stability index of LMS is 5.5481, which is particularly important when preserving the characteristics of the signal over multiple filtering stages.

- The energy retention of FIR is 98,20%, while LMS retains 130.21%. FIR filtering retains almost all the energy of the original signal, whereas LMS tends to amplify the energy, potentially causing distortion in some cases.

Table 1. *Filtering performance and characteristics*

Metric	FIR Filter	LMS Filter
SNR after Filtering (dB)	17.66	9.72
MSE	0.009978	0.062113
Delta Band Power Preservation (%)	100.0%	140.8%

Metric	FIR Filter	LMS Filter
Theta Band Power Preservation (%)	99.7%	138.0%
Alpha Band Power Preservation (%)	99.6%	132.5%
Beta Band Power Preservation (%)	100.3%	105.8%
Processing Time (s)	0.0721	0.0046
Stability Metric	19.2747	5.5481
Energy Preservation (%)	98.20%	130.21%

General evaluation:

- FIR filtering is superior in reproducing the original signal, with much better SNR, MSE, and power preservation. However, the downside is its longer processing time and higher computational requirements.

- LMS filtering has the advantage of much faster processing speed, making it suitable for real-time or resource-limited applications, but it is less accurate in preserving the original signal. Nevertheless, it is still a viable option where speed is a priority.

Our research findings reveal a clear difference in the performance of FIR and LMS filters when applied to the same EEG dataset, thereby confirming the respective strengths and limitations of each technique as follows. Prior studies [1-5] primarily focused on optimizing FIR filters, emphasizing the stability of the frequency response and the precise extraction of features; however, they often neglected to address the dynamic variability of EEG signals over time. In contrast, research on LMS filters [6-10] has demonstrated rapid adaptability, reduced latency, and optimized computational cost in real-time environments, yet it has encountered challenges in ensuring accuracy when analyzing the complex components of the signal. In our study, by applying uniform evaluation criteria, the results indicate that FIR filters maintain a stable frequency response, while LMS filters exhibit superior adaptability and efficiency in processing rapid signal variations. Consequently, this research not only provides specific corroborative data for each method reviewed in the literature [1-10] but also paves the way for a novel approach that combines the advantages of both techniques to optimize the EEG signal denoising process-a facet that previous studies have not comprehensively addressed.

4. CONCLUSION

In this paper, we conducted a comprehensive comparison between the Finite Impulse Response (FIR) filter and the Least Mean Squares (LMS) adaptive filter in the context of noise processing for electroencephalogram (EEG) signals, the removal of 50 Hz power line interference, which in preserving the integrity of critical EEG frequency bands, including Delta, Theta, Alpha, and Beta. The results revealed that the FIR filter significantly enhances the signal-to-noise ratio (SNR) and reduces mean squared error (MSE) compared to the LMS filter. The FIR method effectively maintained the original waveform of the EEG signals, showcasing its robustness in both time and frequency domains. Conversely, while the LMS filter offers advantages in dynamic environments due to its adaptive nature, its performance is heavily influenced by the selection of learning parameters and the quality of the reference signal, resulting in less consistent outcomes in preserving the EEG characteristics.

This study contributes valuable insights into the selection and implementation of filtering methodologies for EEG signal enhancement. Future research directions could involve further exploration of hybrid filtering techniques that combine the strengths of both FIR and LMS methods. Additionally, investigating the application of advanced machine learning algorithms for noise cancellation in EEG signals may yield promising results, particularly in environments with rapidly changing noise conditions.

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THÔNG TIN TÁC GIẢ

Nguyễn Xuân Kiên[1*], Bùi Phương Thảo[1],
Đỗ Văn Đỉnh[2]

**Tác giả liên hệ: nxkien@ictu.edu.vn*

[1]Trường Đại học Công nghệ Thông tin
và Truyền thông, Đại học Thái Nguyên;
[2]Trường Đại học Sao Đỏ.

THỂ LỆ GỬI BÀI
TẠP CHÍ NGHIÊN CỨU KHOA HỌC, TRƯỜNG ĐẠI HỌC SAO ĐỎ

Tạp chí Nghiên cứu khoa học, Trường Đại học Sao Đỏ (P. ISSN 1859-4190, E. ISSN 2815-553X), thường xuyên công bố kết quả, công trình nghiên cứu khoa học và công nghệ của các nhà khoa học, cán bộ, giảng viên, nghiên cứu sinh, học viên cao học, sinh viên ở trong và ngoài nước.

1. Tạp chí xuất bản 01 số/quý bằng hai ngôn ngữ tiếng Việt và tiếng Anh. Tạp chí nhận đăng các bài báo khoa học thuộc các lĩnh vực: Điện - Điện tử - Tự động hóa; Cơ khí - Động lực; Kinh tế; Triết học - Xã hội học - Chính trị học; Các lĩnh vực khác gồm: Công nghệ thông tin; Hóa học - Công nghệ thực phẩm; Ngôn ngữ học; Toán học; Vật lý; Văn hóa - Nghệ thuật - Thể dục thể thao...
2. Bài nhận đăng là những công trình nghiên cứu khoa học chưa công bố trong bất kỳ ấn phẩm khoa học nào.
3. Tòa soạn chỉ nhận bài báo gửi online trên website http://tapchikhcn.saodo.edu.vn. Bài báo gửi về toà soạn dưới dạng file điện tử (*.doc *.docx và *.pdf); cuối bài báo, tác giả ghi rõ thông tin địa chỉ liên hệ, số điện thoại, email và cập nhật thông tin trên website. Bài báo phải được trình bày đúng định dạng, rõ ràng; Trường hợp bài báo phải chỉnh sửa theo thể lệ hoặc theo yêu cầu của Phản biện thì tác giả sẽ cập nhật trên website. Người phản biện sẽ do tòa soạn mời. Tòa soạn không gửi lại bài nếu không được đăng.
4. Các công trình thuộc đề tài nghiên cứu có Cơ quan quản lý cần kèm theo giấy phép cho công bố của cơ quan (Tên đề tài, mã số, tên chủ nhiệm đề tài, cấp quản lý,...).
5. Tên bài báo trình bày bằng hai ngôn ngữ (tiếng Việt và tiếng Anh), font Arial, cỡ chữ 14, in đậm, căn giữa.
6. Tên tác giả (không ghi học hàm, học vị), font Arial, cỡ chữ 10, in đậm, căn lề phải; cơ quan công tác của các tác giả, font Arial, cỡ chữ 9, in nghiêng, căn lề phải.
7. Chữ "Tóm tắt" in đậm, font Arial, cỡ chữ 10; Nội dung tóm tắt của bài báo không quá 10 dòng, trình bày bằng hai ngôn ngữ (tiếng Việt và tiếng Anh), font Arial, cỡ chữ 10, in thường.
8. Chữ "Từ khóa" in đậm, nghiêng, font Arial, cỡ chữ 10; Có từ 03÷05 từ khóa, font Arial, cỡ chữ 10, in nghiêng, ngăn cách nhau bởi dấu chấm phẩy, cuối cùng là dấu chấm.
9. Nội dung bài báo viết bằng tiếng Việt hoặc tiếng Anh; Nếu là bài báo viết bằng tiếng Việt: Tiêu đề tiếng Việt trước, tiếng Anh sau; Tóm tắt tiếng Việt trước, tiếng Anh sau; Từ khóa tiếng Việt trước, tiếng Anh sau; Nếu là bài báo viết bằng tiếng Anh: Tiêu đề tiếng Anh trước, tiếng Việt sau; Tóm tắt tiếng Anh trước, tiếng Việt sau; Từ khóa tiếng Anh trước, tiếng Việt sau.
10. Bài báo được đánh máy trên khổ giấy A4 (21 × 29,7cm) có độ dài không quá 8 trang, font Arial, cỡ chữ 10, giãn dòng At least 12pt, Before 3pt, After 3pt; căn lề trên 2.5cm, dưới 2.5cm, trái 3cm, phải 2cm; hình vẽ phải rõ ràng, đủ nét và được định dạng dưới dạng file ảnh (*.jpg); Phương trình, công thức phải soạn thảo bằng Mathtype hoặc Equation; Phần nội dung bài báo được chia thành 02 cột, khoảng cách cột là 1cm; Trong trường hợp hình vẽ, hình ảnh có kích thước lớn, bảng biểu có độ rộng lớn hoặc công thức, phương trình dài thì cho phép trình bày dưới dạng 01 cột.
11. Tài liệu tham khảo được sắp xếp theo thứ tự tài liệu được trích dẫn trong bài báo.

    - Nếu là sách/luận án: Tên tác giả (năm), Tên sách/luận án/luận văn, Nhà xuất bản/Trường/Viện, lần xuất bản/tái bản.

    - Nếu là bài báo/báo cáo khoa học: Tên tác giả (năm), Tên bài báo/báo cáo, Tạp chí/Hội nghị/Hội thảo, Tập/Kỷ yếu, số, trang.

    - Nếu là trang web: Phải trích dẫn đầy đủ tên website và đường link, ngày cập nhật.
12. Định dạng mẫu bài báo tham khảo tại địa chỉ http://tapchikhcn.saodo.edu.vn/news/detail/198/format_paper

    Bài báo sau khi xuất bản sẽ được công bố trên http://tapchikhcn.saodo.edu.vn.

THÔNG TIN LIÊN HỆ:

Ban Biên tập Tạp chí Nghiên cứu khoa học, Trường Đại học Sao Đỏ

Phòng 203, Tầng 2, Nhà B1, Trường Đại học Sao Đỏ.

Địa chỉ: Số 76, Nguyễn Thị Duệ, Thái Học 2, phường Sao Đỏ, thành phố Chí Linh, tỉnh Hải Dương.

Điện thoại: (0220) 3587213, Fax: (0220) 3882921, Hotline: 0912 107858/0936 847980.

Website: http://tapchikhcn.saodo.edu.vn

Email: tapchikhcn@saodo.edu.vn

BỘ CÔNG THƯƠNG
TRƯỜNG ĐẠI HỌC SAO ĐỎ

Địa chỉ:

- **Số 1:** Số 76, Nguyễn Thị Duệ, Thái Học 2, phường Sao Đỏ, thành phố Chí Linh, tỉnh Hải Dương.
- **Số 2:** Số 72, đường Nguyễn Thái Học, phường Thái Học, thành phố Chí Linh, tỉnh Hải Dương.
- **Điện thoại:** (0220) 3882 269 **Fax:** (0220) 3882 921 **Website:** http://saodo.edu.vn **Email:** info@saodo.edu.vn

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Địa chỉ Tòa soạn:
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Website: http://tapchikhcn.saodo.edu.vn/Email: tapchikhcn@saodo.edu.vn.

Giấy phép xuất bản số: 620/GP-BTTTT ngày 17/9/2021 của Bộ Thông tin và Truyền thông.
In 2.000 bản, khổ 21 × 29,7cm, tại Công ty TNHH in Tre Xanh, cấp ngày 17/02/2011.