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Original Article

The Analysis and Comparison of LMS-Based Filtering Techniques for EEG Signals: Towards Informed Decision Making

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Abstract *- Electroencephalography (EEG) is essential for observing brain activity. It offers non-invasive, high-resolution insights into neural dynamics. Despite its clinical and research applications, EEG signals are prone to noise from powerline interference, muscle artifacts and environmental sources. This study evaluates adaptive filtering techniques—LMS, NLMS, PNLMS and IPNLMS—for denoising EEG signals. A dataset of 23 EEG recordings contaminated with noise was used. Accelerometer signals served as reference inputs. The algorithms were assessed using Mean Squared Error (MSE) Signal-to-Noise Ratio (SNR) and Pearson Correlation Coefficient. PNLMS was found to be the most effective. It achieved the lowest MSE (0.9193), highest SNR (1.0768) and highest correlation (46.9025%). While PNLMS excels in noise reduction it has computational demands that may limit its use in wearable devices. NLMS offers a practical balance. It balances performance and efficiency. Future work includes hybrid algorithms. Real-time implementations will be addressed. Adaptive parameter tuning will also be covered. These aim to enhance EEG signal processing and its applications in clinical and research environments.*

Keywords *- EEG signal, LMS filtering, Motion artifact, NLMS, PNLMS, IPNLMS.*

1. Introduction

Electroencephalography (EEG) is a significant method for brain activity observation and analysis, giving insights into neural dynamics in the highest time resolution without any invasion. Voltage changes are measured by placing electrodes on the scalp, which indicate how ionic currents flow through nerve cells. In neurological diagnosis, cognitive process understanding, and brain computer interface design, among others, this approach is irreplaceable [1]. Clinically, EEG is largely employed to diagnose epilepsy, which is a neurological disorder that causes recurrent seizures. This can be seen by analyzing an EEG to identify definite wave types, such as spikes and sharp waves that suggest epileptic activity [2]. Besides epilepsy, sleep studies often utilize EEG to allow the detection of different sleep stages and as a diagnostic tool for insomnia and sleep apnea [3]. Cognitive neuroscience forms one of the research areas where EEG finds use in studying brain functions related to perception, attention, memory even language processing with real-time data on how the brain reacts to stimuli variation [4].

Despite this, measuring the electrical impulses of the brain using EEG is a very noisy process which can leave them hidden under different varieties of noise. Powerline artifacts, muscle artifacts and environmental noise are the main EEG contaminants. Electrical power grids introduce their own 50 Hz or 60 Hz interference to the system, causing severe artefacts in EEG recordings [5]. Electromyographic (EMG) artifacts, also known as muscle artifacts, are generated by the contraction of skeletal muscles near the electrodes and are superimposed onto brain signals, hence leading to difficulties in the analyses and interpretation of EEG data [6]. Moreover, the environmental noise introduced by different external electromagnetic sources could negatively affect the signal quality.

Due to these challenges, various adaptive filtering techniques have been designed and implemented to improve the EEG signal quality by minimizing noise. Of all these techniques, the LMS algorithm and its derivatives, including the Normalized LMS (NLMS), Proportionate Normalized LMS (PNLMS), and Improved Proportionate Normalized LMS (IPNLMS), are preferred owing to their merits regarding ease of implementation as well as efficiency [7][8]. These algorithms modify the filter coefficients in real-time, enabling them to reduce noise in real-time from EEG data while at the same time reducing the mean squared error between the desired signal and the output [9].

The LMS algorithm was proposed by Widrow and Hoff in 1960 and it is one of the key algorithms of adaptive filtering. It adjusts the filter coefficients in such a way that the difference between the filter output and the desired signal is minimized. However, the LMS algorithm may converge slowly under some conditions and there developed NLMS that normalises the step size to enhance convergence speed and stability [10]. The PNLMS algorithm, which adapts a set of filter coefficients with different step sizes depending on their magnitude, improves performance in sparse environments where only a few coefficients are nonzero [11]. The IPNLMS algorithm improves this approach by adding more constraints for the optimization of convergence speed and steady-state error [12].

The goal of this research is to assess and analyze different LMS-based filtering techniques, including LMS, NLMS, PNLMS, and IPNLMS, to remove noise from EEG signals. By using accelerometer signals as reference inputs, we will evaluate the algorithms' ability to minimize motion artifacts, which is a common source of noise in wearable EEG monitoring systems. The efficiency of these algorithms will be evaluated with the help of indicators such as Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and the Pearson Correlation Coefficient. By conducting this research, we aim to provide insights into the best filtering method for EEG signals so as to enhance the field of EEG signal processing and its usefulness in the medical field and research studies.

2. Adaptive Filtering

Adaptive filtering plays an essential role in many signal processing applications, such as noise suppression, echo removal, and enhancement of the EEG signals. Adaptive filtering is built on the principle that filter coefficients are adjusted constantly with the aim of reducing the error between the desired signal and the output of the filter.

The LMS (Least Mean Squares) algorithm is considered to be at the base of many adaptive filtering techniques, mainly because of its simplicity and efficiency. LMS and its variations introduced in this section can also be applied to other forms of adaptive filtering not restricted to EEG signals. They are also widely used in other biosignals like Electrocardiogram (ECG) and Electromyogram (EMG).

Adaptive filters play an important role in ECG, and they assist in the reduction of noises like powerline interferences and motion interferences which helps in giving accurate diagnosis of heart conditions [13]. Also, in EMG, adaptive filtering helps to filter the disturbing noise from muscle signals which is useful for investigating muscle activity and control [15]. A classic structure for adaptive filtering is shown in Figure 1.

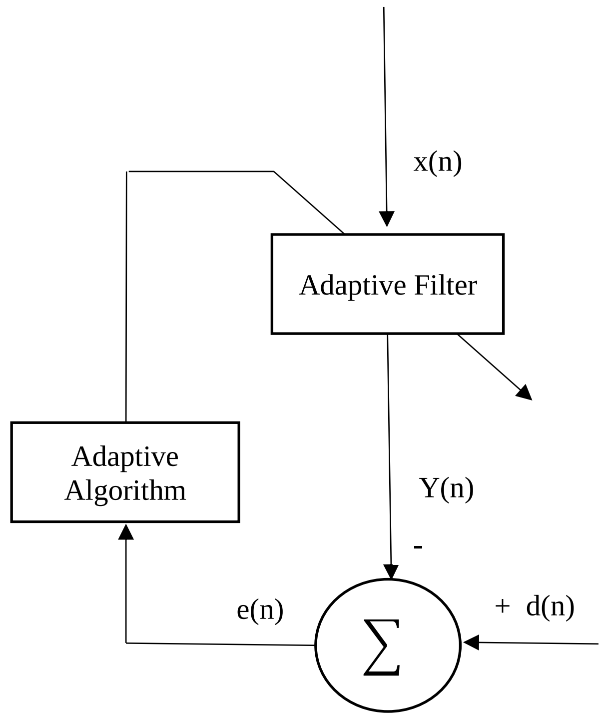

Fig. 1 A classic representation of an adaptive filter

2.1. LMS Algorithm

The LMS algorithm iteratively updates the filter coefficients to minimize the mean squared error. The mathematical formulation is shown in Equation (1):

$$e(n) = d(n) - w^T(n)x(n) \tag{1}$$

Where:

- e(n) is the error signal at iteration n.
- d(n) is the desired signal.
- w(n) is the weight vector at iteration n.
- x(n) is the input vector at iteration n.

And the weight update is in Equation (2):

$$w(n+1) = w(n) + 2\mu e(n)x(n) \tag{2}$$

Constant Mu (μ) controls the convergence speed and stability.

2.2. Normalized LMS (NLMS) Algorithm

NLMS enhances the LMS algorithm by normalizing the step size, which improves convergence stability, especially in scenarios where the input signal power varies significantly. The normalized step size is given in Equation (3):

$$\mu_n = \frac{\mu}{\|x(n)\|^2 + \epsilon} \tag{3}$$

ϵ is a small value to avoid dividing by zero; the weight update is given by Equation (4):

$$\mathrm{w(n+1) = w(n)} + \mu_n \mathrm{e(n)x(n)} \qquad (4)$$

2.3. Proportionate Normalized LMS (PNLMS) Algorithm

PNLMS further refines NLMS by assigning different step sizes to each filter coefficient, which is beneficial for sparse systems where only a few coefficients are significant. The mathematical expression for PNLMS is given by Equation (5):

$$\mu_{n,i} = \frac{\mu(|w_i(n)| + \epsilon)}{\sum_{j=1}^{M}(|w_j(n)| + \epsilon)} \qquad (5)$$

Where i and j denote the indices of the filter coefficients, the weight update is given by Equation (6):

$$w_i(n+1) = w_i(n) + \mu_{n,i} e(n) x_i(n) \qquad (6)$$

2.4. Improved Proportionate Normalized LMS (IPNLMS) Algorithm

IPNLMS incorporates additional constraints to balance the convergence speed and steady-state error, making it suitable for various signal processing applications. The improved step size y given by Equation (7), the weight update remains the same as PNLMS:

$$\mu_{n,i} = \frac{\mu(|w_i(n)| + \epsilon)^{\alpha}}{\sum_{j=1}^{M}(|w_j(n)| + \epsilon)^{\alpha}} \qquad (7)$$

Where alpha (α) is a parameter that adjusts the proportionate effect.

3. Methodology

The dataset used in this study consists of EEG signals contaminated with noise and their corresponding clean EEG signals. Additionally, accelerometer signals were recorded simultaneously to provide reference data for noise suppression. This dataset was contributed to physionet by Kevin Sweeney. The dataset includes 23 recordings, where each recording features a pair of similar physiological signals captured from transducers placed near each other. For each recording, one transducer remains undisturbed, while the other is subjected to manipulation to create motion artifacts with varying durations within every 2 minutes.

The movement of the manipulated transducer and the stability of the other transducer are recorded using 3-axis accelerometers attached to both transducers. [15,16]. The EEG data sampling rate was 2048Hz, and the Accelerometer data sampling rate was 200Hz. To match the EEG signals, the Accelerometer data was digitally resampled. The methodology is shown in Figure 2. The contaminated EEG signal is filtered using every LMS derivative, then the resultant signal is evaluated using Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR) and Pearson Correlation Coefficient. This process was made for each recording, a total of 23 times.

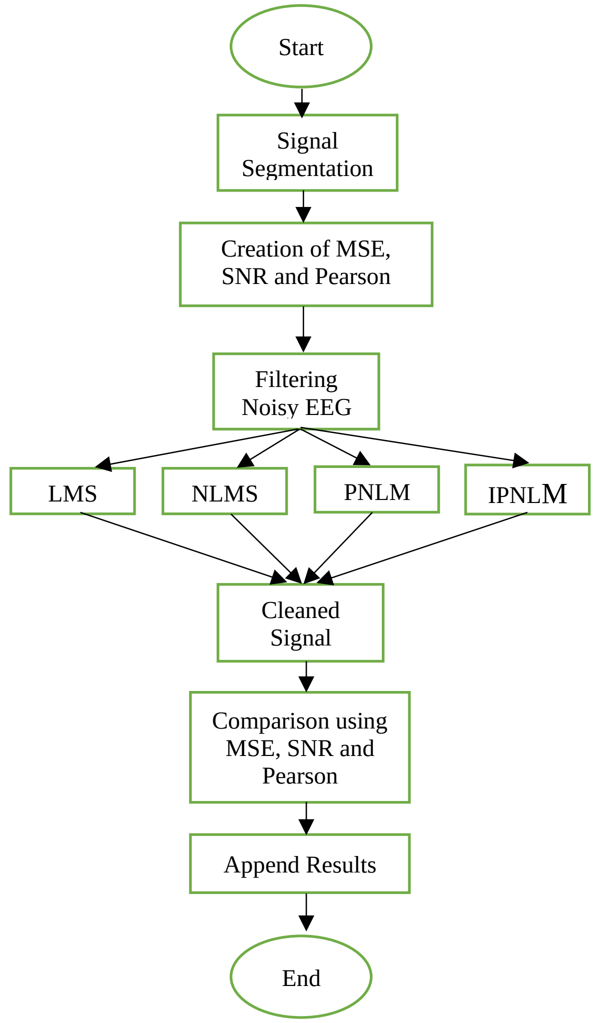

Fig. 2 Methodology diagram

The mathematical definition of the indicators is given by:

- Mean Squared Error (MSE)

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(S_i - \hat{S}_i)^2 \qquad (8)$$

- Signal-to-Noise Ratio (SNR)

$$SNR = 10log_{10}\left(\frac{\sum S_i^2}{\sum(S_i - \hat{S}_i)^2}\right) db \qquad (9)$$

- Pearson Correlation Coefficient

$$r = \frac{\sum(S_i - \bar{S})(\hat{S}_i - \bar{\hat{S}})}{\sqrt{\sum(S_i - \bar{S})^2 \sum(\hat{S}_i - \bar{\hat{S}})}} \qquad (10)$$

Where $\bar{S}$ and $\bar{\hat{S}}$ are the means of the clean and filtered signals, respectively.

4. Results and Discussion

In Figure 3, a segmented signal is shown. From the records, in every signal, the initial rise represents the start of the recording session, and the final fall is the ending of the session. For that reason, the signals were segmented to do the filtering task.

4.1. MSE Results

The results using MSE are shown in Tables 1 and 2. The results show that the LMS algorithm has an average MSE of 0.9817, which is higher than the other algorithms. NLMS shows a lower average MSE of 0.9318, while PNLMS has the lowest MSE at 0.9193. IPNLMS has an average MSE of 0.9506. These results indicate that PNLMS is the most effective in minimizing the error between the clean and filtered signals, making it the superior choice for noise reduction.

4.2. SNR Results

For SNR, a higher value indicates better signal quality. LMS shows an average SNR of 0.5323, NLMS improves this to 0.6453, and PNLMS achieves the highest SNR at 1.0768. IPNLMS has an SNR of 0.8757. These results reinforce that PNLMS significantly enhances the signal-to-noise ratio, thus providing the clearest EEG signals among the algorithms tested.

4.3. Pearson Correlation Coefficient

The Pearson Correlation Coefficient results show that LMS achieves an average correlation of 1.85%, while NLMS improves this to 39.44%. PNLMS has the highest correlation at 46.9025%, with IPNLMS close behind at 45.1815%. These correlations indicate how well the filtered signals match the clean signals, with PNLMS again proving to be the most effective.

However, indeed, if we think about the application of these algorithms to wearable devices, the issues of complexity, energy consumption and memory are key. The LMS method is the least complex in terms of computation. It can be used in devices with low computational power but provides the lowest noise suppression capability among the three methods. In comparison to LMS, NLMS has a better stability and convergence rate but a slightly higher computational complexity. The proposed algorithm, PNLMS, has the lowest MSE, highest SNR, and correlation coefficient, with the drawback of high computational complexity due to the variable step size calculation. While the convergence speed and steady-state error of the algorithm are jointly optimized, the IPNLMS is still less efficient in terms of computational complexity than NLMS or LMS. Even though the PNLMS algorithm has a higher computational complexity as compared to the other algorithms it offers the best solution for reconstructing the quality of the EEG signals. This makes it suitable for use in fields where precise determination of the signals is necessary, as in the case of health diagnose and research. However, the computational complexities that arise can reduce its application in restricted wearables such as smart wristbands. Thus, NLMS has good potential in many practical applications, as it provides good performance while keeping the amount of computations within reasonable levels. In Figure 4, a comparative view of all the LMS derivatives is shown. Individually, the graphs por each LMS derivative are shown in Figures 5, 6,7 and 8.

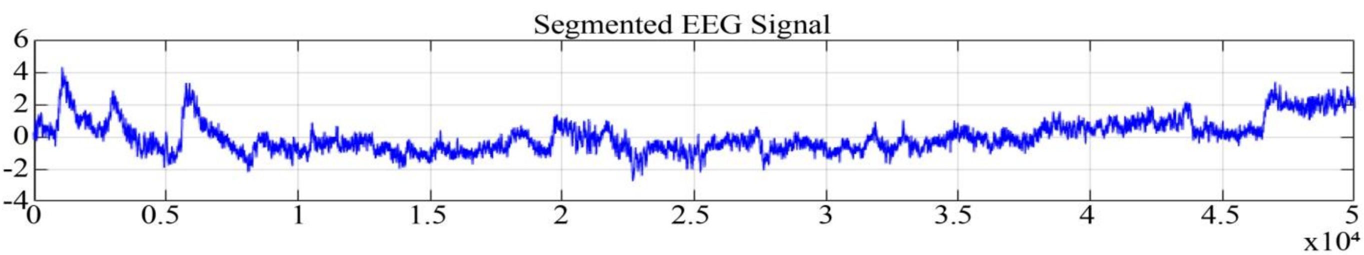

Fig. 3 Segmented EEG signal

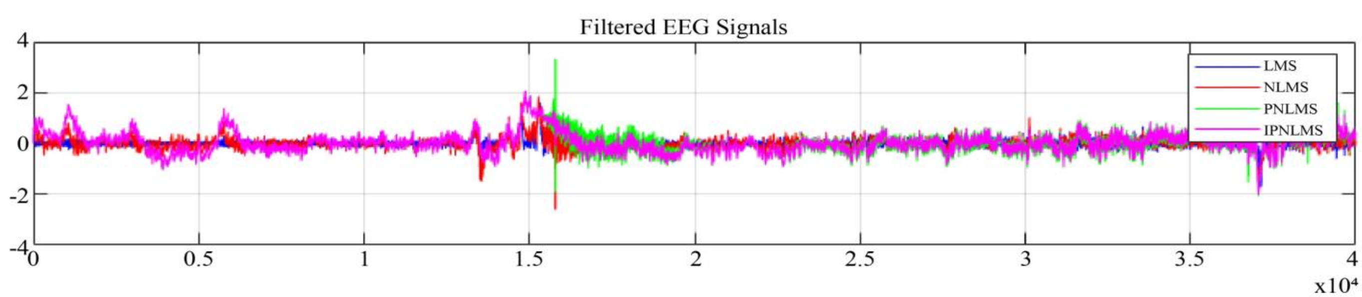

Fig. 4 Comparative view of the results for each LMS-derivative

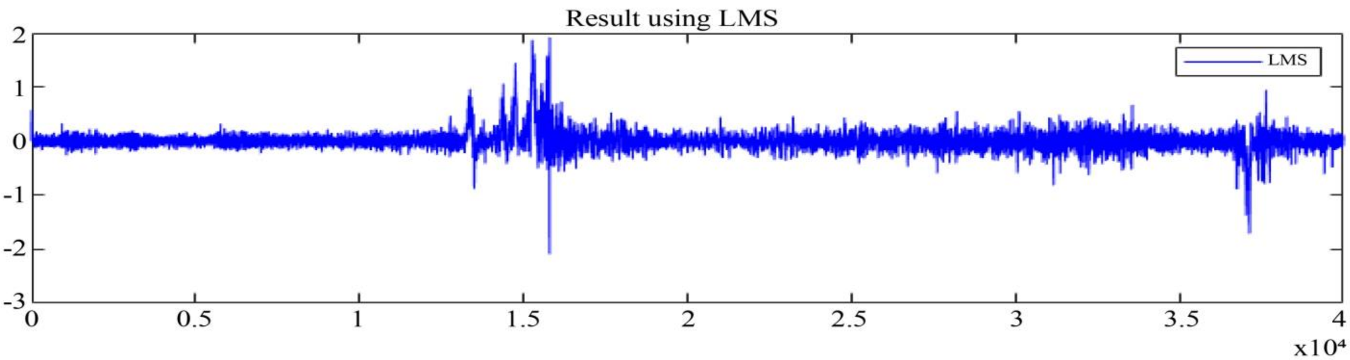

Fig. 5 Result using LMS

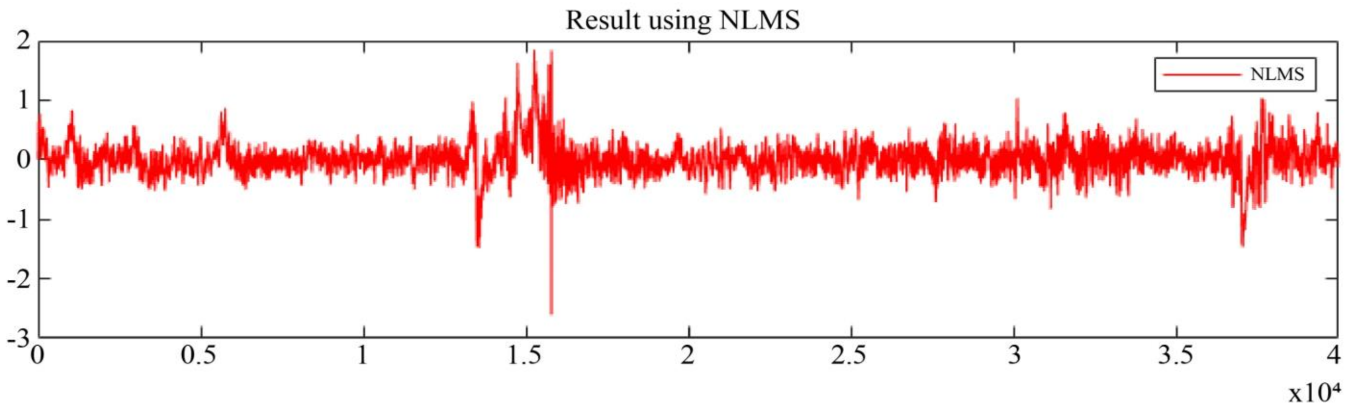

Fig. 6 Result using NLMS

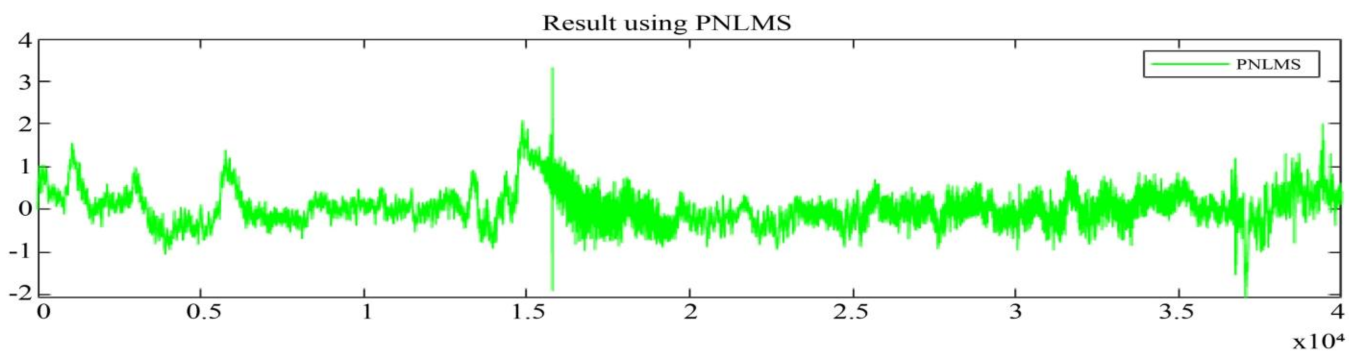

Fig. 7 Result using PNLMS

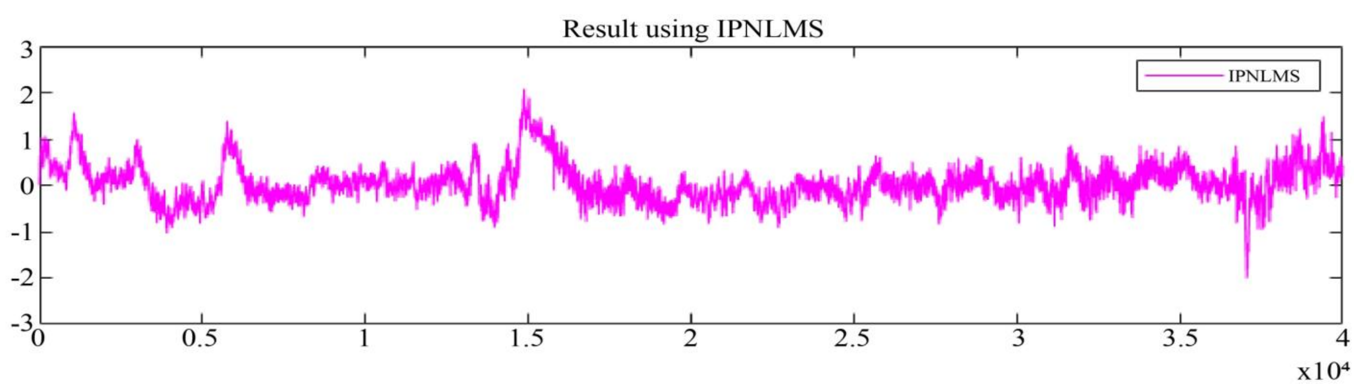

Fig. 8 Result using IPNLMS

5. Conclusion

In this study, the use of LMS and its derivatives also proved to be effective on EEG signals in addition to the tests already performed on ECG signals [17]. The PNLMS has been found to be the best suitable for improving the EEG signal quality equal to or better than LMS, NLMS, and IPNLMS for all tested parameters. However, it has a higher computational complexity compared to the other methods analyzed above. However, the overall results in terms of MSE, SNR, and Pearson Correlation Coefficient suggest that this method can indeed be useful in applications requiring high signal fidelity. Therefore, in order to have a practical implementation of such underlining computational algorithms into wearable devices, there is a need to seek for an optimization between performance and resource usage. As such, NLMS is shown to present a practical solution that has more than reasonable learning performance to computational load ratio.

Further research could expand the study of adaptive filtering algorithms in a number of directions toward enhancing the performance's applicability in the analysis of EEG signals. There are also trends in combining the above algorithms, for example, the creation of PNLMS and IPNLMS structures when new algorithms will select the best features of these algorithms and provide increased speed and an even greater level of noise suppression. Further, precise implementations of the proposed algorithms in the real-time environment of wearable devices should be designed and implemented in order to assess the possible real-life characteristics of such algorithms, their computational cost, and power requirements. As mentioned above, some successful approaches to the noise environment, which can be utilized in tuning algorithm parameters according to the characteristics of incoming signals, can be considered for enhancing adaptability.

One possible direction to bring improvements to the filtering step is to use huge databases along with advanced types of machine learning to forecast and prevent noise traces in EEG signals. Some of the possibilities for future work consist of the enhancement of these adaptative filtering techniques to other biosignals, including the ECG and the EMG, with the aim of comparing their performances in various physiological environments. There is a need for long-term longitudinal investigations that will determine the AL stability and its durability, more particularly considering its applicability in situations where motion related disturbances dominate, such as in ambulatory monitoring. In the subsequent research, more efforts can be made to improve the reliability and applicability of adaptive filtering methods, making a solid foundation for further developed biosignals processing in clinic and Internet use health preservation sphere.

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Appendix

Table 1. First 12 MSE results

	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10	Trial 11	Trial 12
LMS	0.8417	1.1217	2.0493	0.8581	1.0748	0.8968	1.0343	1.1503	1.1535	0.8877	0.7122	0.9352
NLMS	0.7924	1.4608	1.5497	0.7825	1.0530	0.7920	0.9114	1.1401	1.2058	0.9557	0.6037	0.8452
PNLMS	0.7446	1.8987	2.0151	0.5649	0.9980	0.6041	0.7528	1.1710	1.1552	0.9717	0.6850	0.7335
IPNLMS	0.7598	1.8743	2.0029	0.5758	1.0313	0.6053	0.7731	1.2000	1.1884	1.0427	0.7393	0.8183

Table 2. Last 11 MSE results

	Trial 13	Trial 14	Trial 15	Trial 16	Trial 17	Trial 18	Trial 19	Trial 20	Trial 21	Trial 22	Trial 23
LMS	1.1512	**1.3310**	0.8615	0.4212	0.2607	0.5928	1.8214	1.6044	0.9622	1.2627	1.2696
NLMS	0.8324	1.2248	0.5782	0.4029	0.3734	0.3316	1.6384	1.0002	0.9212	1.0905	0.9467
PNLMS	0.7738	1.0029	0.5281	0.1585	0.2652	0.2328	1.9087	1.2149	0.7867	1.1741	0.8042
IPNLMS	0.8288	1.0015	0.5867	0.1787	0.2749	0.2756	1.9437	1.2361	0.8275	1.3046	0.7937

Table 3. First 12 SNR results

	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10	Trial 11	Trial 12
LMS	0.5630	0.7534	0.4790	0.7615	0.6211	0.7220	0.3317,	0.7904	0.3617	0.4153	0.3071	0.4751
NLMS	1.0104	-1.6461	-1.9025	1.0651	-0.2243	1.0124	0.4029	-0.5696	-0.8127	0.1966	2.1920	0.7304
PNLMS	1.2808	-2.7846	-3.0431	2.4801	0.0086	2.1885	1.2329	-0.6858	-0.6266	0.1246	1.6429	1.3461
IPNLMS	1.1930	-2.7285	-3.0166	2.3970	-0.1338	2.1800	1.1174	-0.7920	-0.7496	-0.1818	1.3115	0.8706

Table 4. Last 11 SNR results

	Trial 13	Trial 14	Trial 15	Trial 16	Trial 17	Trial 18	Trial 19	Trial 20	Trial 21	Trial 22	Trial 23
LMS	0.6505	0.3390	0.3309	0.5773	0.3991	0.3561	0.3258	0.6079	0.4810	0.6818	0.9122
NLMS	0.7967	-0.8806	2.3788	3.9484	4.2787	4.7934	-2.1443	-0.0011	0.3566	-0.3765	0.2376
PNLMS	1.1133	-0.0129	2.7731	7.9985	5.7639	6.3292	-2.8075	-0.8455	1.0416	-0.6971	0.9465
IPNLMS	0.8153	-0.0067	2.3155	7.4797	5.6075	5.5973	-2.8863	-0.9207	0.8223	-1.1548	1.0035

Table 5. First 12 Pearson results

	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10	Trial 11	Trial 12
LMS	2.9113	0.8220	0.2247	0.1998	0.1622	0.0954	0.1652	0.0711	0.4948	38.2196	0.1136	0.0040
NLMS	48.5158	15.6567	4.9012	56.9916	6.1885	49.8048	37.0514	22.2416	32.3234	35.3301	67.8858	50.4164
PNLMS	55.9935	11.8004	-5.2813	71.9275	20.0666	64.8368	54.1016	26.6618	40.9684	39.3597	65.4666	62.6967
IPNLMS	54.6440	14.5047	-4.2343	71.5969	15.1869	64.8634	52.6756	24.6112	37.0223	34.5845	63.4285	59.4907

Table 6. Last 11 Pearson results

	Trial 13	Trial 14	Trial 15	Trial 16	Trial 17	Trial 18	Trial 19	Trial 20	Trial 21	Trial 22	Trial 23
LMS	0.3102	0.3037	1.8000	0.4280	5.6170	0.1837	0.0341	0.0054	0.3630	0.0060	3.1047
NLMS	51.8084	6.7013	68.4057	77.6688	80.0986	83.5446	8.9517	19.5878	36.8437	23.0263	23.2001
PNLMS	57.8589	32.7083	73.4841	91.7586	86.4511	88.7678	0.7690	11.3287	51.4588	31.0110	44.5629
IPNLMS	55.0711	32.5913	70.9420	90.6645	85.9431	86.9081	0.9886	9.6112	48.4875	23.7143	45.8777