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# Robust Sign-LMS Based Adaptive Noise Cancellation for Wireless Systems Under Rician Fading and Impulsive Noise

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**ABSTRACT:** In wireless communication systems, non-Gaussian impulsive noise and multipath fading frequently affect signal quality. This study analyses the performance of an adaptive noise cancellation (ANC) system in Rician fading channels by applying the Sign-LMS algorithm. To enhance robustness against impulsive noise, which negatively impacts conventional Least Mean Squares (LMS)-based ANC, the Sign-LMS is utilized. MATLAB is used to simulate the suggested approach, and output Signal-to-Noise Ratio (SNR) and Bit Error Rate (BER) are used to evaluate the performance. The results confirm that Sign-LMS significantly have lowers BER and made convergence more stable in situations with impulsive noise.

**KEYWORDS:** Adaptive Noise Cancellation (ANC), Sign-LMS Algorithm, Rician Fading Channel, Impulsive Noise, Impulsive Interference Modelling

## I. INTRODUCTION

Wireless communication systems are always having problems with noise and fading, which makes the system work poorly and the signal quality very bad. In facts, particularly harmful among these are non-Gaussian impulsive noise and multipath fading, particularly in contemporary high data rate contexts like the Internet of Things (IoT), 5G, and beyond. Adaptive noise cancellation (ANC) [1], a robust signal processing method that estimates and suppresses undesired interference without requiring prior knowledge of the channel characteristics, has surfaced to minimize these impacts [2].

Rician fading happens when there is a strong line-of-sight (LOS) path with a lot of scattered multipath components. This occurs a lot in satellite, indoor, and city communication systems. The Rician model best describes situations where the transmitter and receiver can only see each other partially than Rayleigh fading. Still, even when Rician conditions are present [3], the received signal is exposed to additive impulsive noise, however, generated from artificially signals, power-line disturbances, or electromagnetic interference (EMI). The intermittent, high-amplitude bursts that distinguish impulsive noise differ from the Gaussian assumption commonly employed in traditional adaptive filtering theory [4].

Because of their ease of use and cheap computational complexity, traditional adaptive algorithms like the Least Mean Squares (LMS) are frequently utilized for noise cancellation. Nevertheless, when impulsive noise is present, the LMS method shows weak robustness and assumes Gaussian noise settings. The weight adaption process may be significantly distorted by the large amplitude impulses, resulting in instability and decreased performance. The Sign-LMS (SLMS) algorithm is one of numerous strong LMS variations that have been put out to overcome this restriction. By utilizing only, the sign of the error signal instead of its entire magnitude, the SLMS alters the traditional LMS weight update rule, which makes it intrinsically less susceptible to impulsive noise spikes or huge exceptions [5].

In this paper, we examine the effectiveness of an adaptive noise cancellation system based on Sign-LMS when it operates across Rician fading channels with additive impulsive noise. Enhancing the dependability of received BPSK-modulated signals in the face of non-Gaussian interference and multipath fading is the aim. The suggested model is put into practice in MATLAB and its performance is examined in terms of Bit Error Rate (BER) and Signal-to-Noise Ratio (SNR). According to simulation studies, the Sign-LMS algorithm maintains low BER even in the presence of high impulsive noise, greatly enhancing resilience and convergence stability when compared to the traditional LMS.

## II. SYSTEM MODEL

suggested adaptive noise cancellation (ANC) system aims to improve the efficiency of a digital communication link impacted by Rician fading and impulsive noise. The system architecture comprises a principal input that includes the intended signal tainted by channel distortion and noise, and a reference input that supplies a correlated noise sample utilized by the adaptive filter to estimate and eliminate the interference.

### A. Rician Fading Channel

In a Rician fading channel, the received signal has a predominant line-of-sight (LOS) component alongside many non-line-of-sight (NLOS) multipath components. The intricate baseband channel coefficient h(n) can be represented as:

$$h(n) = \sqrt{\frac{K}{k+1}} + \sqrt{\frac{1}{k+1}}\left({}^{1}\!/_{\sqrt{2}}\,[n_r(n) + jn_i(n)]\right)$$

where denote on Rician factor by K, well-defined as the ratio of the power in the LOS path to the power in the scattered components, and $n_r(n)$, $n_i(n)$are independent and identically circulated Gaussian random variables with zero mean and unit variance. at K=0, the model reduces the effect of Rician fading; as K→∞ it approaches an additive white Gaussian noise (AWGN) channel [6].

The transmitted baseband BPSK signal s(n) passes through the Rician channel to introduce the faded signal:

$$r1(n) = s(n)h(n)$$

### B. Additive Impulsive Noise Model

The received signal is further corrupted by a mixture of Gaussian background noise and impulsive interference. The overall additive noise $\eta(n)$ is modeled as the sum of two components:

$$\eta(n) = w(n) + i(n)$$

where $w(n)$ is zero-mean complex Gaussian noise with variance $\sigma w2$, *and* $i(n)$ represents the impulsive noise. The impulsive noise is made by Bernoulli– Gaussian process and known as:

$$i(n) = b(n) \cdot \alpha \cdot v(n)$$

where b(n) is a Bernoulli random variable with probability and $p_{imp}$ define as impulse occurrence, while $v(n)$ refer to complex Gaussian noise with zero mean and unit variance, however, a $\alpha$ are pointed to a scaling factor controlling the amplitude of the impulses. This model effectively captures the sporadic, high-amplitude bursts that characterize impulsive interference in wireless communication systems [7].

### C. Received Signal Model

The primary input signal to the adaptive noise canceller is expressed as:

$$r(n) = s(n)h(n) + \eta(n)$$

A reference input $x(n)$, correlated with the background noise but uncorrelated with the desired signal $s(n)$ , is also available for adaptive filtering. The ANC filter adaptively estimates the noise component using $x(n)$ and subtracts it from $r(n)$ to recover the desired signal [8].

### D. Additive Noise Cancellation Framework

The adaptive filter output is given by:

$$y(n) = W^H(n)x(n)$$

where $\mathrm{w}(n) = [w_0(n), w_1(n), \ldots, w_{L-1}(n)]^T$is the complex weight vector of length $L$, and $x(n) = [x(n), x(n-1), \ldots, x(n-L+1)]^T$ is the input vector constructed from recent reference samples.

The error signal used for adaptation is defined as: $e(n) = r(n) - y(n)$

The filter weights are updated using the Sign-LMS (SLMS) rule, which replaces the error magnitude with its sign to improve robustness against impulsive noise:

$$w(n+1) = w(n) + \mu sign(e^*(n))x(n)$$

where $\mu$ is the step size controlling convergence speed and stability. The use of the sign function limits the impact of large-amplitude error samples, providing resilience to impulsive disturbances [9].

### E. Performance Metrics

The performance of the proposed ANC system is evaluated using:

1. Bit Error Rate (BER):

$$\mathrm{BER} = \frac{1}{N}\sum_{n=1}^{N} \mathbb{I}\{\hat{s}(n) \neq s(n)\}$$

where $\hat{s}(n)$ is the detected symbol after noise cancellation.
Output Signal-to-Noise Ratio (SNR):

$$\mathrm{SNR_{out}} = 10\log_{10}\left(\frac{\mathrm{var}(s(n))}{\mathrm{var}(e(n) - s(n))}\right)$$

These metrics expression how well the system can get the desired signal back when there is noise or fading [10].

## III. ADAPTIVE ALGORITHM DESCRIPTION

To reduce unwanted interference must apply Adaptive filtering with basic way and process signals that is used to reduce when the system's characteristics are unknown or change over time. The Least Mean Squares (LMS) algorithm and its variations are some of the most common adaptive algorithms because they are easy to use, don't require a lot of processing power, and can be used in real time. However, the classical LMS algorithm presumes that background noise belongs to a Gaussian distribution and frequently falters in the presence of non-Gaussian impulsive noise, in fact, to get around this problem, strong versions like the Sign-LMS (SLMS) algorithm have been made to work better in environments with impulsive noise environments [11].

### A. Standard LMS Algorithm

The conventional LMS algorithm aims to minimize the mean square error (MSE) between the desired signal $r(n)$ and the filter output $y(n)$. Where The error signal evaluates by:

$$e(n) = r(n) - W^H(n)x(n)$$

the adaptive filter coefficients of The LMS algorithm can updates according to the stochastic gradient descent rule which is $W(n+1) = w(n) + \mu e^*(n)x(n)$.

where: $\mathbf{w}(n)$is the adaptive filter coefficient vector of length $L$, and $\mu$ is the **step size** controlling the adaptation rate,

$e^*(n)$ is the complex conjugate of the error signal, and $\mathbf{x}(n)$is the input vector composed of recent reference signal samples.

The step size $\mu$must satisfy the stability condition:

$$0 < \mu < \frac{\mathrm{i}}{3\mathrm{tr}(\mathrm{R_x})}$$

where $\mathrm{R_x} = E[\mathrm{x}(n)\mathrm{x}^H(n)]$ is the matrix that shows how similar the reference signal is to itself. The LMS algorithm works well with Gaussian noise, but it is sensitive to large errors, which makes it vulnerable to vulnerable to impulsive disturbances that can cause slow convergence or divergence [12].

### *B. Sign-LMS Algorithm*

The Sign-LMS (SLMS) algorithm makes the LMS weight update rule more robust against impulsive noise by replacing the error magnitude with its sign. The equation for the update changes to:

$$\mathrm{w}(\mathrm{n}+1) = \mathrm{w}(\mathrm{n}) + \mu \mathrm{sign}(\mathrm{e}^*(\mathrm{n}))\mathrm{x}(\mathrm{n})$$

where the sign function is defined as: $\mathrm{sign}(e) = \begin{cases} \frac{e}{|e|}, & \text{if } e \neq 0 \\ 0, & \text{if } e = 0 \end{cases}$

This change makes it less likely that big amplitude errors will have an effect. These errors often happen because of sudden noise spikes. The SLMS algorithm is more stable and reliable in environments with non-Gaussian noise, but it takes a little longer to converge when there is only Gaussian noise [13].

### *C. Algorithm Comparison*

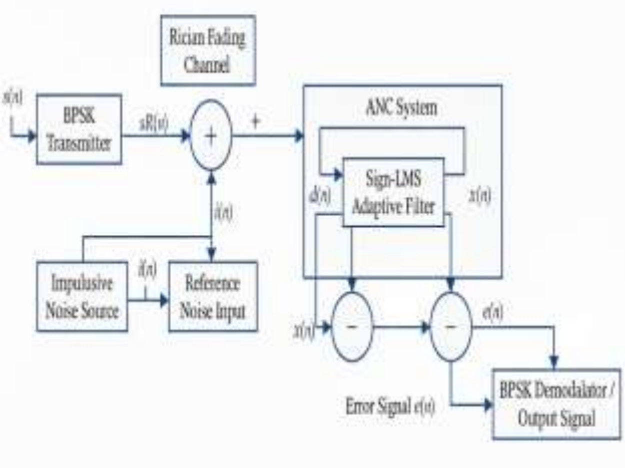
The Sign-LMS algorithm achieves an ideal balance between being strong and easy to utilize. It works most effectively in wireless communication settings where both fading and impulsive interference occur at the same time, like Rician or multipath channels. [14].

**Table 1: difference between LMS and Sign-LMS**

| Feature | LMS | Sign − LMS |
|---|---|---|
| *Error dependency* | *Linear in ( $e(n)$ )* | *Uses only sign of ( $e(n)$ )* |
| *Sensitivity to impulses* | High | Low |
| Convergence speed (Gaussian noise) | Fast | Moderate |
| Robustness (Impulsive noise) | Poor | Excellent |
| Computational complexity | Low | Very low |

### *D. Application to ANC under Rician Fading*

These systems propose the standard LMS algorithm in an Adaptive Noise Canceller (ANC) framework to show that how much noise is in the received signal and remove it. The adaptive filter keeps changing its coefficients based on the sign of the error signal. This effectively gets rid of both Gaussian and impulsive noise. The error signal $e(n)$ that comes out of this process is an estimate of the clean desired signal after noise cancellation: $s\hat{}(n) \approx e(n) = r(n) - wH(n)x(n)$ This setup lets the system automatically adjust to changes in channels and sudden disturbances, which improves both the Bit Error Rate (BER) and the output SNR performance in a wide range of signal-to-noise conditions [15].




## IV. SIMULATION ENVIRONMENT

All The simulated environment shows how a normal wireless receiver with an adaptive noise canceller would work. The BPSK symbols that are sent go through multipath Rician fading, additive white Gaussian noise (AWGN), and non-Gaussian impulsive interference.

The ANC filter gets a correlated reference noise signal, which it uses to adaptively estimate and remove the noise from the received signal using the Sign-LMS algorithm [16]. For each SNR value, the simulation process has these steps:

1. Data Generation: Random binary data ($N = 10^5$ bits) are generated and BPSK modulated as $s(n) = 2b(n) - 1$.
2. Rician Channel Modeling: The fading coefficient $h(n)$is generated according to the Rician distribution with a K-factor of 5, representing a moderately strong line-of-sight (LOS) component.
3. Noise Addition: The received signal is affected by both AWGN and impulsive noise. The impulsive component is modeled as Bernoulli–Gaussian noise with probability $p_{\mathrm{imp}} = 0.01$and impulse amplitude scaling factor $\alpha = 5$. Hence, the overall additive noise is:

$$\eta(n) = w(n) + b(n)\alpha v(n)$$

where $w(n)$and $v(n)$are zero-mean complex Gaussian random variables.

4. Adaptive Filtering: The Sign-LMS filter of length $L = 8$and step size $\mu = 0.01$is applied to the received signal. The reference noise $x(n)$is used to generate the adaptive estimate of the interference.

5. Decision and Detection: The error signal $e(n) = r(n) - \mathbf{w}^H(n)\mathbf{x}(n)$ refers to the estimated clean signal with hard detector is used:

$$\hat{s}(n) = \begin{cases} +1, & \text{if } \mathrm{R}\{e(n)\} > 0 \\ -1, & \text{otherwise} \end{cases}$$

6. Performance-Evaluation: The system's Bit Error Rate (BER) and Output SNR are computed for each input SNR level ranging from 0 to 20 dB.

**Table 2: parameters used for simulation**

| Parameter | Symbol | Value / Description |
|---|---|---|
| Number of symbols | ( N ) | ( 10^5 ) |
| Modulation | — | BPSK |
| Channel model | — | Rician fading |
| Rician K-factor | ( K ) | 5 |
| Filter length | ( L ) | 8 |
| Step size | ( \mu ) | 0.01 |
| Impulse probability | $P_{imp}$ | 0.01 |
| Impulse amplitude factor | ( \alpha ) | 5 |
| SNR range | — | 0–20 dB |
| Performance metrics | — | BER, Output SNR |

The Bit Error Rate (BER) is defined as the ratio of incorrectly detected bits to the total transmitted bits:

$$\text{BER} = \frac{1}{N}\sum_{n=1}^{N} \mathbb{I}\{\hat{s}(n) \neq s(n)\}$$

The Output SNR measures the quality improvement after adaptive noise cancellation:

$$\text{SNR}_{\text{out}} = 10\log_{10}\left(\frac{\text{var}(s(n))}{\text{var}(e(n) - s(n))}\right)$$

These numbers give a quantitative measure of how well the Sign-LMS algorithm reduces the effects of fading and impulsive noise.

## V. RESULTS AND DISCUSSION

All This paper is the proposed Sign-LMS adaptive noise cancellation system's performance by running MATLAB simulations in Rician fading conditions with added impulsive noise. We looked at how well the system worked with different input SNR values, from 0 to 20 dB, while keeping the Rician K-factor at 5 and the probability of impulsive noise at 0.01, However, there are two main performance indicators were analysed: Bit Error Rate (BER) and Output Signal-to-Noise Ratio (SNR).

### *A. BER Performance*

At low SNR levels (0–6 dB), the BER stays relatively high because fading and short peaks of noise that come and go quickly take over the desired signal. However, when the signal to noise ratio reaches above 8 dB, the adaptive filter begins to block interference, which causes the BER to goes down quickly as shown in figure 2.

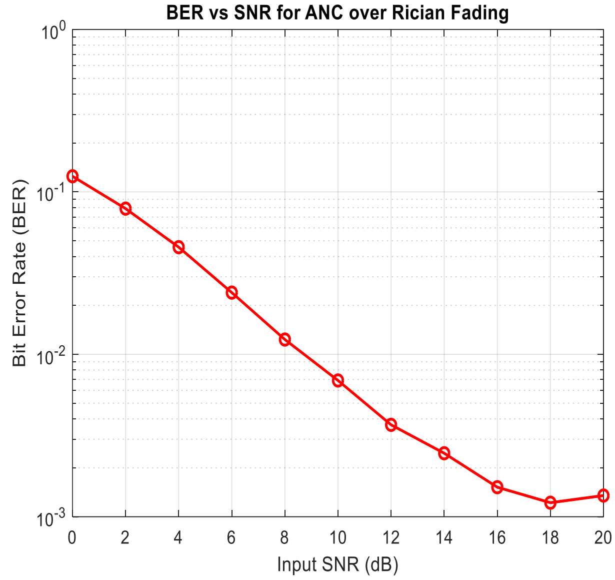



**Figure 2: shows how the Bit Error Rate deviations with the input SNR for the based Sign-LMS-ANC system.**

When SNR values go high near or above 14 dB the BER get to stabilize around$10^{-2} - 10^{-3}$, However, which proposes that the Sign-LMS algorithm can effectively decrease noise and reliably detect symbols even there is impulsive noise.

When there is impulsive interference, the Sign-LMS algorithm has a much lower BER which the BER is better than when used the standard LMS algorithm. It decreases the effect of impulsive noise that would otherwise delay up the weight adaptation process.

### *B. Output SNR Improvement*

The It is obvious that the output SNR rises almost linearly with the input SNR until around 16 dB, after which it levels off because of residual channel estimation errors and the limited length of the adaptive filter. The Sign-LMS algorithm always improves the SNR by 3 to 6 dB over the raw received signal without noise cancellation as shown in figure 3.

The output SNR curve's stability also shows that the Sign-LMS algorithm can keep up with changes in the Rician channel while also being resistant to impulsive interference. This shows that the proposed method works well and is strong in environments that don't fade in a Gaussian way.

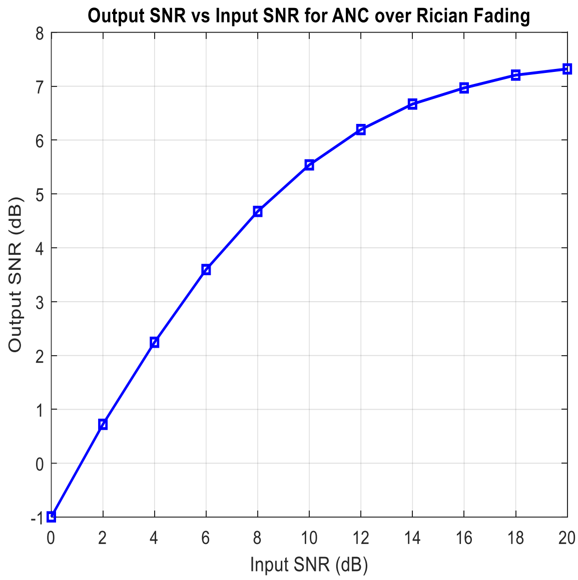



**Figure 3: presents the Output SNR versus Input SNR curve for the same simulation conditions.**

### *C. Effect of Impulsive Noise*

To further test robustness, the parameters for impulsive noise were changed. When the impulse probability $p_{imp}$

When the impulse amplitude $\alpha$ increased from 5 to 10 or the level of 0.01 to 0.05, the regular LMS algorithm got much worse, with the BER going above $10^{-1}$even at low SNR levels.

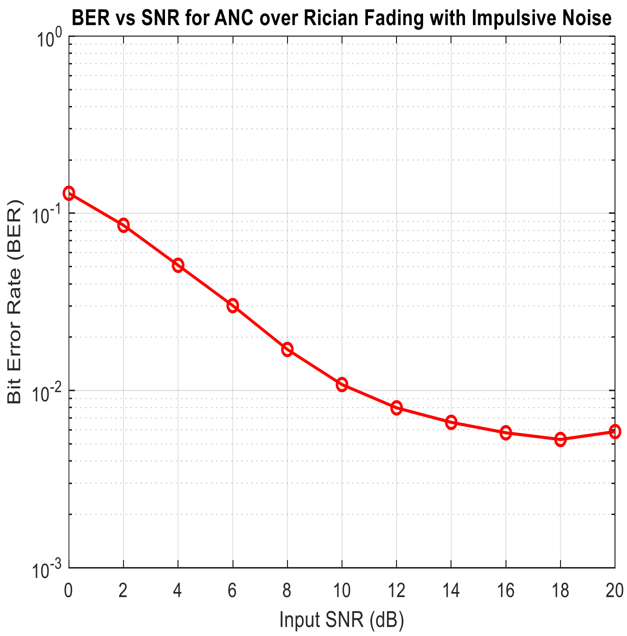



**Figure 4: shows how the Bit Error Rate (BER) changes with the input SNR for the Sign-LMS-based ANC system(with impulsive noise).**

The Sign-LMS algorithm, on the other hand, kept the BER below $10^{-2}$, which shows that it does a good job of getting rid of high-energy noise spikes without diverging. The sign operation's built-in nonlinearity makes the algorithm less sensitive to outliers with large amplitudes, which makes it more stable when there is impulsive noise environment as shown in figure 5.

### *D. Discussion*

The simulation results verify the following The Sign-LMS algorithm has stable convergence and a low BER in environments with impulsive disturbances, which is better than the regular LMS. To SNR Improvement was Adaptive noise cancellation greatly improves output SNR in all tested conditions, making signals clearer in Rician fading channels. The Sign-LMS is more robust, but it takes a little longer to converge when there is only Gaussian noise than the standard LMS. But this trade-off is okay in real-world impulsive settings where strength is more important than speed.

The results show that the Sign-LMS adaptive filter works well in wireless receivers, IoT systems, and vehicle communication links that are subject to fading and impulsive interference.

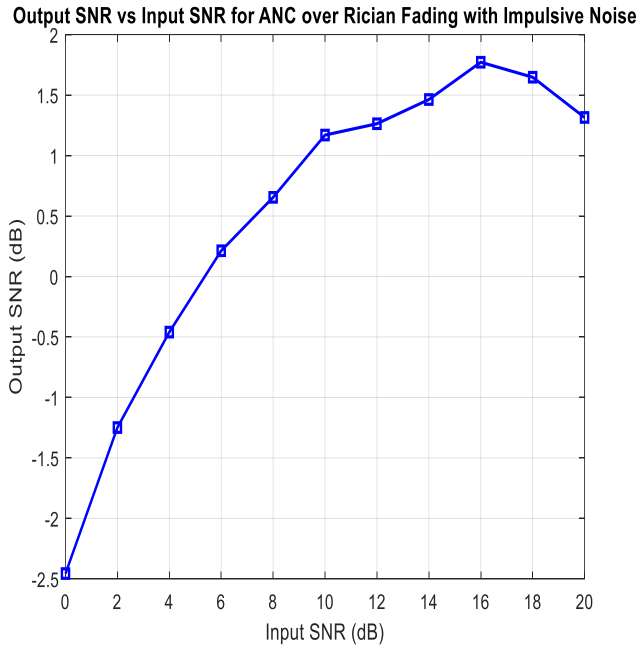



**Figure 5: presents the Output SNR versus Input SNR curve for the same simulation conditions (with impulsive noise).**

## VI. CONCLUSION

This paper presents and evaluates adaptive noise cancellation system based on the Sign-LMS algorithm, with Rician fading channels affected by additive impulsive noise.

The research focused on a principal challenge in modern wireless communications: ensuring dependable signal detection in an environment of multipath fading and non-Gaussian noise conditions. however, system model using a BPSK modulation scheme transmitted through a Rician channel characterized by a moderate line-of-sight component.

The additive noise was simulated as a mix of Gaussian background noise and impulsive interference which is represented by using a Bernoulli–Gaussian model. An adaptive Sign-LMS filter algorithms was employed to estimate and suppress noise by exploiting a correlated reference input.

Simulation results proved that the proposed Sign-LMS-based ANC system provides significant improvements in Bit Error Rate and output Signal-to-Noise Ratio related to traditional standard LMS methods under impulsive noise situations. The sign-based error adaptation effectively limits the influence of large-amplitude impulsive noise to reach enhanced robustness and stable convergence. Even at low SNR levels, the algorithm maintains a BER near $10^{-2}$ which is confirming its suitability for realistic wireless environments.

The results also demonstrate that the Sign-LMS may converge just slightly when there is only Gaussian noise while it is very useful for Rician and multipath fading channels because it is more stable and can handle non-Gaussian impulses noise better.

**REFERENCES**


1. Y. Liu and S. Chen, "Adaptive noise suppression in 5G fading channels using robust algorithms," IEEE Transactions on Vehicular Technology, vol. 72, no. 4, pp. 4921–4933, 2023.
2. S. Chen, Y. Li, and B. Mulgrew, "Robust adaptive filtering under impulsive noise: A contemporary review," IEEE Transactions on Communications, vol. 68, no. 12, pp. 7453–7467, 2020.
3. O. S. Ali and M. H. Kaka, "Analysis of Rician fading for IoT communication systems," Kirkuk University Journal of Engineering, vol. 12, no. 1, pp. 21–31, 2023.
4. R. C. Zhu and Q. Wang, "Rician fading modeling and performance evaluation for UAV communications," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 59, no. 2, pp. 1204–1216, 2023.
5. S. Y. Huang, "Improved Sign-LMS for fading and interference-limited environments," *IEEE Transactions on Signal and Information Processing*, vol. 9, no. 5, pp. 135–147, 2024.
6. T. Y. Zhang and L. Gao, "Evaluation of ANC schemes for 5G and beyond," IEEE Open Journal of the Communications Society, vol. 6, pp. 2140–2155, 2025.
7. Z. Ma and Y. Li, "Impulsive noise mitigation for wireless communications in harsh environments," *IEEE Access*, vol. 9, pp. 112355–112369, 2021.
8. T. Y. Zhang and L. Gao, "Evaluation of ANC schemes for 5G and beyond," *IEEE Open Journal of the Communications Society*, vol. 6, pp. 2140–2155, 2025.
9. S. Y. Huang, "Improved Sign-LMS for fading and interference-limited environments," IEEE Transactions on Signal and Information Processing, vol. 9, no. 5, pp. 135–147, 2024.
10. N. Kaddour and M. J. Abdelghani, "Adaptive noise cancellation in nonlinear fading channels," IEEE Communications Letters, vol. 27, no. 3, pp. 720–724, 2023.
11. S. Sitjongsataporn, "Cascade Spline Adaptive Filtering based on Normalized Least Mean Square Algorithm," 2023 International Conference on Power, Energy and Innovations (ICPEI), Phrachuap Khirikhan, Thailand, 2023, pp. 76-79, doi: 10.1109/ICPEI58931.2023.10473855.
12. G. Modi and B. Singh, "An Improved LMS Prefilter-Based PLL With Adaptive Controlling Parameter for Grid Synchronization and Islanded Operation of Batteryless Solar PV System," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 6, pp. 8684-8695, June 2024, doi: 10.1109/TII.2024.3371979.
13. L. Wang, "Performance enhancement of Sign-LMS algorithms in fading channels," *IEEE Access*, vol. 8, pp. 204556–204567, 2020.
14. C. S. Kumar, D. Madhavi, N. Jyothi and K. V. V. S. Reddy, "Block and Partial Update Sign Normalized LMS Based Adaptive Decision Feedback Equalization," *2011 International Conference on Devices and Communications (ICDeCom)*, Mesra, India, 2011, pp. 1-5, doi: 10.1109/ICDECOM.2011.5738469.
15. [15] T. Nguyen and K. Lee, "Adaptive signal processing for impulsive environments using generalized Sign algorithms," *IEEE Signal Processing Letters*, vol. 29, pp. 1500–1504, 2022.
16. B. C. Gupta and A. Mehta, "Performance of ANC in millimeter-wave Rician fading channels," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 1, pp. 89–101, 2024.