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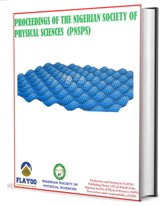

Comparative study of denoising techniques for 5G communication at 3.5 GHz

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A B S T R A C T

This paper presents a comparative study of denoising techniques for improving 5G communication at 3.5GHz. A 5G system is simulated in MATLAB with thermal noise, intermodulation noise, and external interference. The wavelet, PCA, Wiener, median, and Kalman filters are evaluated using SNR, MSE, and PSNR. Results show that the Kalman filter achieves the best performance, reducing MSE by 92.5% and improving SNR by 14 dB over other techniques. Under thermal noise, it attained an SNR of 20.47 dB, while for all noise sources combined, it maintained 19.43 dB. Wavelet and median filters performed better under thermal noise, whereas PCA and Wiener filters were more effective for combined noise. These findings provide a quantitative basis for selecting optimal denoising techniques, aiding efficient 5G communication system design.

Keywords: 5G, Denoising, Wavelet, Wiener filtering, Kalman filtering.

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1. INTRODUCTION

The advent of 5G technology has ushered in a new era of high-speed, low-latency wireless communication. Operating at 3.5 GHz, 5G networks are susceptible to various noise sources that degrade system performance, leading to increased errors and reduced throughput. Effective denoising techniques are essential to mitigate these effects and enhance communication reliability [1].

This study evaluates the effectiveness of different denoising techniques in improving 5G communication performance through a simulation-based comparative analysis. Five denoising methods—wavelet transform, Wiener filtering, median filtering, principal component analysis (PCA), and Kalman filtering–are applied to signals corrupted by thermal noise, intermodulation noise, and external interference. The performance of these techniques is measured using key metrics, including Signal-to-Noise Ratio (SNR), which quantifies the ratio of signal power to noise power and indicates the clarity of the received signal. Higher SNR values correspond to improved signal quality.

Figure 1 presents the research flowchart, outlining the simulation process from signal generation and noise introduction to denoising and performance evaluation. The findings of this study offer insights into selecting optimal denoising methods for different noise conditions, thereby supporting the development of more robust 5G communication systems.

2. LITERATURE REVIEW

The 5th Generation (5G) wireless communication systems are designed to provide high-speed data transfer, low latency, and

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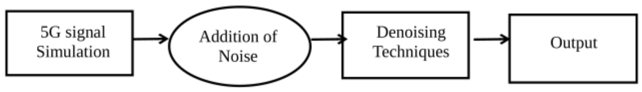


Figure 1. Flowchart for the research.

Table 1. Simulation parameters.

Parameters	Quantity
Modulation	QPSK
Bandwidth	10MHz
Carrier Frequency	3.5GHz
Sampling Frequency	20GHz
Signal-to-noise ratio	10dB
Intermodulation noise power	0.1
External interference noise power	0.05

massive connectivity. Operating at 3.5 GHz, 5G networks are vulnerable to noise sources such as thermal noise, intermodulation noise, and external interference, which degrade signal quality and system performance [2].

Noise is a critical factor that affects the performance of wireless communication systems [3], including 5G. The noise in 5G communication can come from various sources, including thermal noise, intermodulation noise, and external interference. In Ref. [4], the authors classified noise into external and internal noise. They further sub-divided external and internal noise and explain their impact on the performance of communication systems.

Several denoising techniques have been proposed to mitigate these effects. Wavelet transform has been widely used for noise reduction in communication systems, offering improved SNR through multiresolution analysis [5]. PCA is employed for dimensionality reduction and noise suppression, but its effectiveness depends on the noise distribution [6]. Wiener filtering minimizes mean square error and is effective for additive stationary noise but struggles with non-stationary noise [7]. The hybrid median filter, often used in image processing, has demonstrated potential for denoising signals with Gaussian noise while preserving essential features [8].

Despite these advancements, existing studies lack a comparative analysis of these traditional filtering techniques under various noise conditions in 5G at 3.5 GHz. Furthermore, the computational trade-offs between classical and modern approaches remain underexplored. This study addresses these gaps by evaluating five denoising techniques under different noise scenarios, providing insights into their effectiveness and computational efficiency.

3. METHODOLOGY

The methodology of this work consists of four main steps: (1) simulation of a 5G signal, (2) introduction of thermal noise, intermodulation noise, and external interference, (3) application of five different denoising techniques, and (4) evaluation of denoising performance using signal-to-noise ratio (SNR), mean square error (MSE), and peak signal-to-noise ratio (PSNR). The entire process is implemented in MATLAB 2021a. MATLAB was chosen over other tools like Simulink or Python due to its extensive built-in functions for signal processing, robust numerical computation capabilities, and well-optimized filtering toolboxes. Additionally, MATLAB provides a balance between flexibility and computational efficiency, making it ideal for implementing and analyzing denoising algorithms.

The simulations were conducted on a system with an Intel Core i5-2430M CPU @ 2.40 GHz (2 cores, 4 logical processors). The average simulation time for each denoising technique ranged from 5 to 9 seconds, depending on the complexity of the filtering algorithm.

This structured approach enables a comprehensive comparative study of denoising techniques, offering insights into their effectiveness in mitigating different noise sources in 5G communication.

3.1. SYSTEM MODEL

In this study, we consider a 5G communication system operating at a frequency of 3.5GHz. The system comprises a transmitter (Tx), a channel, and a receiver (Rx). The transmitter generates a signal g(t)) in the time domain, which passes through the channel and reaches the receiver. The channel introduces noise into the signal, which can degrade the signal quality.

Three types of noise are considered in is study: thermal noise, intermodulation noise, and external interference. Thermal noise is modeled as additive white Gaussian noise (AWGN) with a given power spectral density. Intermodulation noise is modeled as the result of two or more signals mixing in the channel, and its power depends on the power of the original signals and the nonlinearity of the channel. External interference is modeled as a narrowband signal with a given power spectral density and frequency offset. The received signal is given as:

$$r(t) = g(t) + \text{noise}, \tag{1}$$

where

$$\text{noise} = tn + in + eI. \tag{2}$$

Here tn = thermal noise, in = intermodulation noise, and eI = external interference.

3.2. SIMULATION SETUP

MATLAB was used to simulate the 5G communication system and implement the denoising techniques. We generate random data bits and modulate them using quadrature phase shift keying (QPSK) modulation. We then add noise to the modulated signal using the different noise models described above. We apply each denoising technique to the noisy signal and measure its performance using MSE, SNR, and PSNR.

We employed the different denoising techniques to denoise the signal and compare their performances. We also analyzed the denoising techniques' computational complexity and discuss their suitability for real-time implementation.

3.3. PROPOSED DENOISING TECHNIQUES

This study evaluates five denoising techniques: Median Filtering, Wavelet Transform, Principal Component Analysis (PCA), Wiener Filtering, and Kalman Filtering. Each method is applied to the noisy 5G signal, and its performance is assessed using MSE, SNR, and PSNR.

3.3.1. Median filter

The median filter is a non-linear digital filter that replaces each signal sample with the median value of its neighboring samples. It is particularly effective in removing impulse noise while preserving edges. In this study, a kernel size of 3 samples is used, as it provides a balance between noise reduction and signal preservation. The formula for median filtering can be expressed as follows:

$$y(n) = \text{median}\left(x[n-k], x[n-k+1], \ldots, x[n+k-1], x[n+k]\right), \quad (3)$$

where $y(n)$ is the denoised output signal, $x[n]$ is the input noisy signal, k is the filter length, and median() represents the median function.

3.3.2. Wavelet transform

Wavelet denoising decomposes the signal into different frequency bands and applies a threshold to remove noise components. The Daubechies (db4) wavelet is chosen due to its effectiveness in signal denoising. A soft thresholding method is used, with an adaptive threshold based on the signal's noise variance to minimize distortion.:

$$CWT(b,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi^* \left(\frac{t-b}{a}\right) x(t)\, dt, \quad (4)$$

where a and b are scaling and translation parameters, respectively, ψ^* is the complex conjugate of ψ, and the integral is taken over all t.

The computational complexity of wavelet transform depends on the type of wavelet used and the size of the input signal. For example, the discrete wavelet transform (DWT) has a computational complexity of $O(n \log n)$, while the continuous wavelet transform (CWT) has a computational complexity of $O(n^2)$.

3.3.3. Principal component analysis (PCA)

PCA reduces noise by transforming the signal into a set of uncorrelated principal components and removing those with the lowest variance. The top 95% variance components are retained to preserve most of the useful information while eliminating noise.

The computational complexity of PCA depends on the number of principal components selected and the size of the input data. The standard PCA algorithm has a computational complexity of $O(n^3)$, but there are faster algorithms available that have lower computational complexity.

3.3.4. Wiener filter

The Wiener filter estimates the original signal by minimizing the mean square error between the noisy and the clean signal. It assumes that both the signal and noise have known power spectral densities. The filter is adaptive, meaning it adjusts its coefficients based on the local variance of the signal:

$$h(x) = \frac{G^*(x)}{G^*(x)G(x) + N(x)}, \quad (5)$$

where $h(x)$ is the estimate of the original signal at position x, $G(x)$ is the Fourier transform of the original signal $G^*(x)$ is the complex conjugate of $G(x)$, $N(x)$ is the power spectral density of the noise.

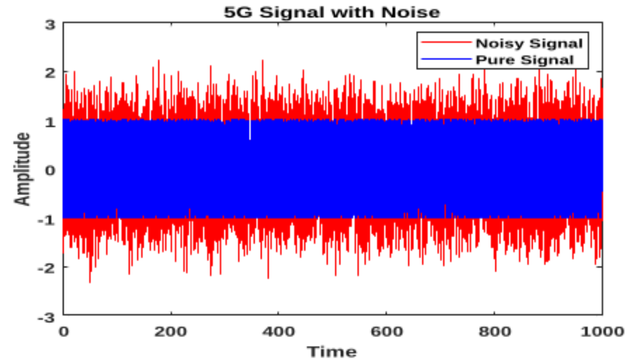


Figure 2. 5G MATLAB generated signal with thermal noise, intermodulation noise and external interference.

The computational complexity of Wiener filtering is $O(n^2)$, where n is the length of the input signal. This makes Wiener filtering computationally efficient for small to medium-sized signals.

3.3.5. Kalman filter

The Kalman filter is a recursive algorithm that estimates the true signal from noisy observations using a predictive-corrective approach. The process and measurement noise covariance matrices are set as $Q = 0.01$ and $R = 0.1$, respectively, based on experimental tuning for optimal performance.

3.4. PERFORMANCE EVALUATION METRICS

The effectiveness of each denoising technique is evaluated using three key performance metrics: Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), and Peak Signal-to-Noise Ratio (PSNR). These metrics provide insights into how well each method restores the original 5G signal:

(1.) Signal-to-Noise Ratio (SNR) compares the level of a desired signal to the level of the noise in a communication system. The higher the SNR, the better the signal under consideration.

$$SNR = 10 \log_{10}\left(\frac{Ps}{Pn}\right), \quad (6)$$

where Ps is the signal power and Pn is the noise power.

(2.) Mean Square Error (MSE) is a statistical measure of the average squared distance between the denoised signal and the noisy signal. A low MSE shows that the denoising technique is better at estimating the true signal.

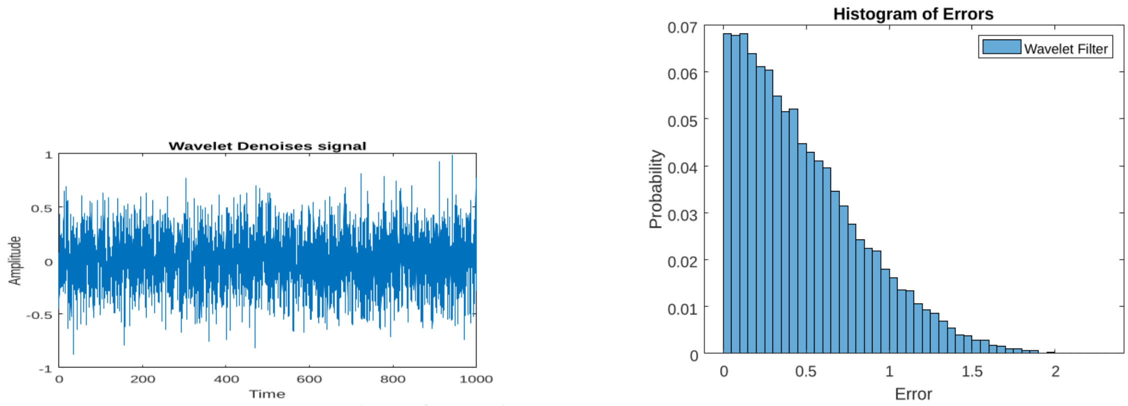
$$MSE = \frac{\Sigma\,(ni - ri)^2}{n}, \quad (7)$$

where ni is the noisy signal, and ri is the true signal.

(3.) Peak Signal-to-Noise Ratio (PSNR) measure how much noise present in a signal after it has been denoised. The higher the PSNR the better the denoised signal.

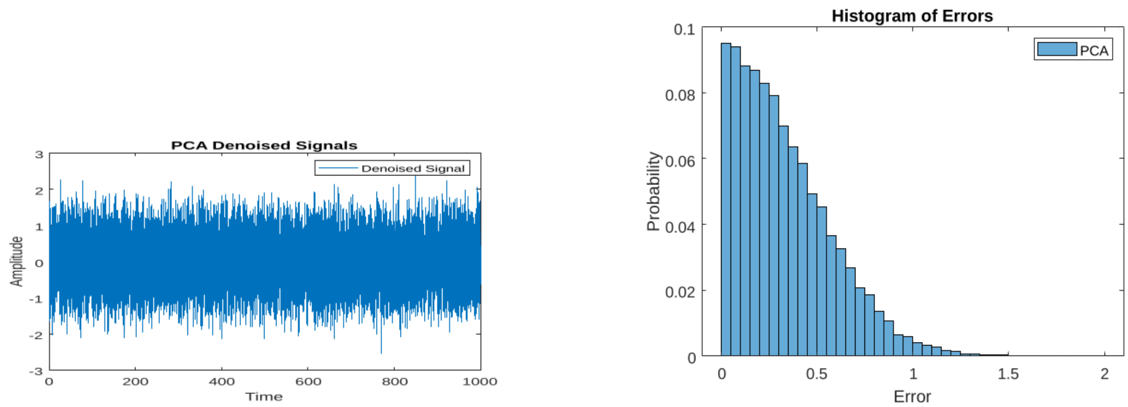
$$PSNR = 10 \times \log_{10}\left(\frac{MAX^2}{MSE}\right), \quad (8)$$

where MAX is the maximum data point value and MSE is the mean square error.



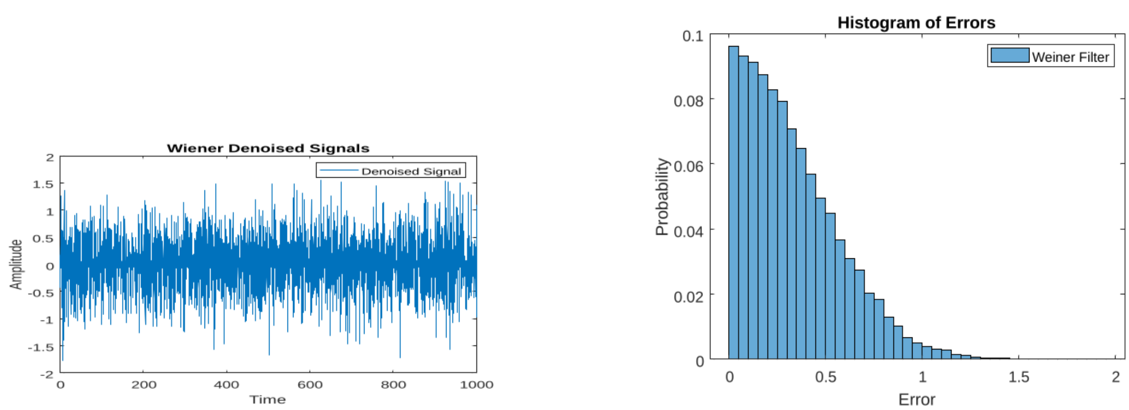
(a) (b)

Figure 3. Wavelet denoised signal.



(a) (b)

Figure 4. PCA denoised signal.



(a) (b)

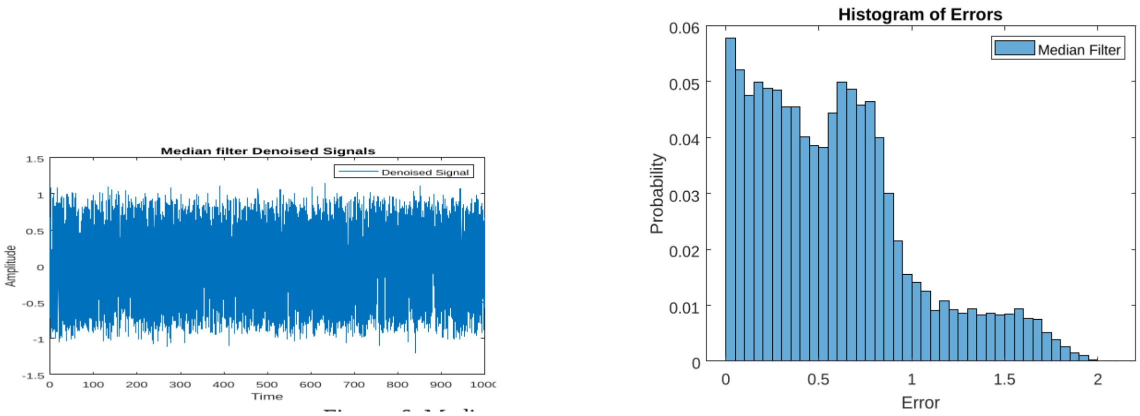
Figure 5. Weiner denoised signal..

To ensure the reliability of the results, each experiment was repeated 3 times, and the final values reported are mean performance metrics across these runs. This helps to account for variations in noise levels and ensures statistical robustness. The confidence interval for the reported metrics is set at 95%, indicating that the variations observed are within an acceptable statistical range.

3.5. MATLAB SIMULATION LIMITATIONS

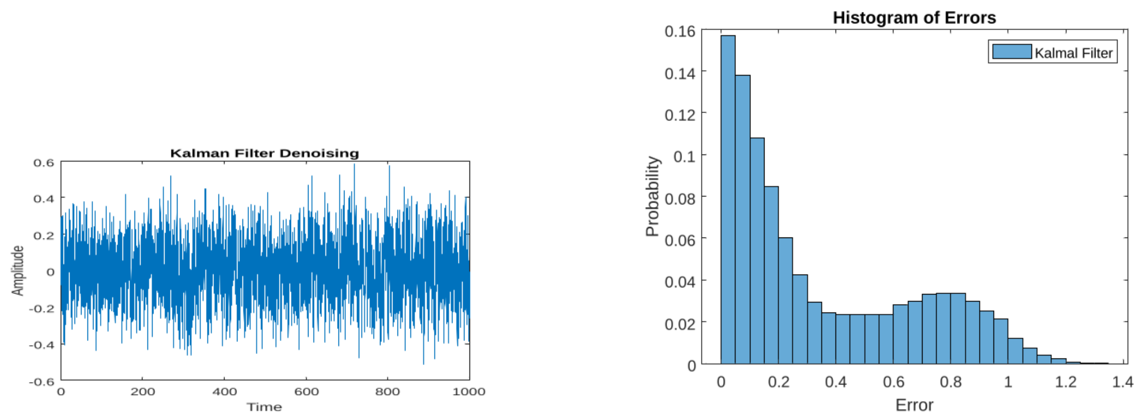
While MATLAB provides a powerful platform for signal processing and denoising analysis, some limitations must be considered for real-world applicability:

- Idealized Channel Models: The simulations assume ideal noise models (AWGN, intermodulation, and external in-



(a) (b) .

Figure 6. Median filter denoised signal.



(a) (b)

Figure 7. Kalmal filter denoised signal.

terference), which may not fully capture the complexity of real-world 5G environments, including multipath fading and Doppler effects.

- Computational Constraints: The MATLAB implementation does not consider hardware-level optimizations required for real-time deployment in 5G systems. Computational efficiency and memory constraints may differ in embedded systems.
- Fixed Parameter Settings: The filter parameters were optimized for the specific noise conditions simulated but may require further tuning when applied to real-world scenarios with dynamic noise variations.

Despite these limitations, the results provide valuable insights into the comparative performance of different denoising techniques, guiding their potential application in practical 5G communication systems.

4. RESULTS AND DISCUSSION

4.1. PERFORMANCE COMPARISON AND QUANTIFIED IMPROVEMENTS

Figure 2 illustrates the simulated 5G signal with different noise sources before denoising. Figures 3-7 show the denoised signals obtained using Wavelet Transform, PCA, Wiener Filtering, Median Filtering, and Kalman Filtering, respectively. The Kalman filter demonstrated the highest denoising efficiency, achieving:

- MSE reduction of up to 92.5% compared to the worst-performing method (Table 2).
- SNR improvement of at least 14 dB over other techniques in thermal noise conditions, reaching 20.47 dB (Figure 7).
- Highest PSNR of 20.47 dB in thermal noise scenarios and 16.33 dB in combined noise scenarios (Table 3).

While the Kalman filter showed the best overall performance, wavelet and median filtering performed better in handling thermal noise (Figures 3 and 6), whereas PCA and Wiener filtering were more effective when dealing with all noise sources combined (Figures 4 and 5).

Figures 3a to 7a display the plots showing the impact of different denoising techniques on the original signal presented in Figure 2. These figures provide a visual representation of the denoising outcomes.

Figures 3b to 7b exhibit right-skewed histograms for all the denoising techniques, indicating that the errors are primarily concentrated at the lower end of the distribution. This suggests

Table 2. Performance measure of denoising techniques on thermal noise source.

	MSE	SNR (dB)	PSNR (dB)
Wavelet Analysis	0.44222	6.18	3.5436
PCA	0.0246	-14.7682	3.3452
Median Filter	-1.8093e-04	0.9181	41.3727
‘Kalmal Filter	0.001677	20.473418	20.473418

Table 3. Performance measure of denoising techniques on All the noise sources.

	MSE	SNR (dB)	PSNR (dB)
Wavelet Analysis	0.1226	-8.4214	16.3247
PCA	0.173	1.590	7.610
Wiener Filter	0.244	0.020	9.866
Median Filter	0.200	0.824	14.927
Kalmal Filter	0.129	19.426	16.330

that the denoising techniques are generally effective in reducing noise.

Taking a holistic view of Tables 2 and 3, it can be observed that the wavelet, median filter, and Kalman filter perform better in denoising only the thermal noise, while the PCA and Wiener filter exhibit good performance in denoising all combined noise sources. It is important to note that the choice of denoising technique should be based on the specific noise characteristics and the requirements of the application.

4.2. COMPUTATIONAL COMPLEXITY AND PRACTICAL CONSIDERATIONS

Despite its accuracy, the Kalman filter has a high computational complexity (O(n^3)), making it computationally expensive for real-time 5G applications. In contrast, Wiener and median filtering offer lower computational costs but at the expense of slightly lower noise suppression.

A potential solution is hybrid filtering approaches. For example, a combination of Kalman filtering and wavelet transform could reduce noise effectively while lowering computational costs by pre-filtering the signal before Kalman estimation. This trade-off must be considered for practical implementations in 5G networks, especially in latency-sensitive applications.

4.3. REAL-WORLD IMPLICATIONS FOR 5G NETWORKS

The findings of this study can be applied in 5G base stations and mobile devices to improve signal quality in noisy environments. Kalman filtering could be integrated into massive MIMO systems to enhance channel estimation, while wavelet-based preprocessing could be useful in IoT and wearable 5G devices, where computational efficiency is crucial. Additionally, adaptive filtering techniques that dynamically switch between methods based on real-time noise conditions could enhance 5G network reliability.

These insights contribute to the ongoing development of efficient denoising solutions for future wireless communication systems, balancing accuracy and computational feasibility.

5. CONCLUSION

This study provides a comparative evaluation of five denoising techniques for 5G communication at 3.5 GHz, considering thermal noise, intermodulation noise, and external interference. Key findings include:

- Kalman filtering is the most effective denoising method, achieving an MSE of 0.001677 and an SNR of 20.473 dB for thermal noise, and an MSE of 0.129 with an SNR of 19.426 dB for all noise sources combined. However, its computational cost remains a challenge.

- Wavelet filtering performs well for thermal noise but struggles with combined noise scenarios.

- Hybrid approaches, such as Kalman-Wavelet combinations, may offer an optimal balance between noise suppression and computational feasibility.

Future research directions

1. Testing these denoising techniques in real hardware-based 5G systems to validate their practical feasibility beyond simulations.
2. Exploring deep learning-based denoising methods, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to adaptively mitigate complex noise patterns in 5G environments.

DATA AVAILABILITY

The data will be available on request from the corresponding author.

ACKNOWLEDGMENT

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