

Denoising microwave interferometry data for high-Rise buildings with CEEMDAN energy-Correlation dual Criteria

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Abstract

High rise buildings are key components of urban infrastructure, and accurate monitoring of their dynamic responses under wind and seismic loads is essential for structural safety assessment. Ground based interferometric radar system has become an effective tool for displacement monitoring due to its high precision, non-contact operation, and full field measurement capability. However, practical measurements are often contaminated by thermal noise, atmospheric phase delays, and multipath effects, resulting in strong nonstationary and nonlinear characteristics that limit the accuracy of dynamic parameter identification and micro deformation extraction. To address this issue, this study proposes an adaptive denoising method based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and a dual criterion of energy and correlation. The method first applies CEEMDAN to suppress mode mixing and separate multi frequency components. A joint energy–correlation criterion is then introduced to adaptively distinguish noise dominated and structural response dominated intrinsic mode functions (IMFs), enabling effective noise removal while preserving essential signal information. Using micro deformation data from the CCTV Tower as a case study, the proposed method is compared with wavelet denoising and Kalman filtering. Results demonstrate that the proposed approach effectively suppresses noise while preserving waveform characteristics, peak amplitudes, and energy distribution, providing a reliable solution for radar based structural monitoring of high-rise buildings.

1. Introduction

With the continuous advancement of urbanization, high rise buildings have become integral components of modern cityscapes and critical urban infrastructure (Campbell et al., 2005). Their structural integrity is fundamentally linked to operational safety and public well-being. However, under diverse excitations including wind loads, seismic activity, and ambient vibrations, high rise structures are susceptible to cumulative damage, which may precipitate catastrophic failure (Farahani et al., 2023). Consequently, the implementation of long term, real time, and high precision Structural Health Monitoring (SHM) is of paramount engineering and societal importance. By acquiring reliable structural dynamic response data, key modal parameters such as natural frequencies and damping ratios can be identified, enabling robust safety assessments and early hazard warnings to inform maintenance strategies (Deng et al., 2023).

Currently, time series displacement acquisition for high rise buildings is primarily conducted via contact based and non-contact approaches. Contact based monitoring employs sensors such as accelerometers, strain gauges, and fiber optic sensors directly installed on the structure (Xiang et al., 2017). While these techniques provide direct measurements, they are often constrained by limited spatial coverage, high installation complexity, and potential long term reliability issues. In contrast, non-contact techniques including Global Navigation Satellite Systems GNSS, Terrestrial Laser Scanning TLS, and Interferometric Synthetic Aperture Radar InSAR enable remote sensing without physical structural attachment (Hsieh et al., 2006; Negulescu et al., 2013). Despite their versatility, individual non-contact methods often struggle to simultaneously achieve the high precision and high sampling frequencies

required for comprehensive structural performance analysis. Ground based interferometric radar system has recently emerged as a compelling solution, offering high precision, full field, and all weather measurement capabilities (Ferretti et al., 2001).

In practical engineering contexts, however, radar monitoring data are often severely contaminated by complex noise, including system thermal noise, atmospheric turbulence-induced phase perturbations, and multipath effects from building surfaces. These factors render the retrieved displacement signals highly non-stationary and nonlinear. Atmospheric disturbances are particularly problematic; spatiotemporal variations in temperature, humidity, and pressure induce random phase delays, resulting in low-frequency, large-amplitude systematic errors. Furthermore, complex scattering properties introduce random phase noise that masks subtle structural vibrations, thereby compromising the accuracy of modal parameter identification and micro-deformation retrieval.

Conventional denoising methods such as band pass filtering, wavelet thresholding, and Kalman filtering exhibit distinct limitations when processing such signals. Band pass filtering is computationally efficient but requires prior knowledge of the target frequency range and fails when signal and noise spectra overlap. Wavelet thresholding offers multi scale analysis, yet its performance is highly sensitive to the subjective selection of wavelet bases and decomposition levels, often leading to signal distortion. Kalman filtering, while theoretically robust, depends heavily on an accurate state space model. However, establishing such models for complex high-rise structures characterized by multi modal coupling and geometric nonlinearities remains a

formidable challenge. Thus, there is an urgent need for advanced adaptive denoising approaches.

Empirical Mode Decomposition (EMD), proposed by Huang et al., is a data-driven, adaptive time-frequency analysis method that decomposes nonlinear signals into Intrinsic Mode Functions (IMFs). Despite its utility, EMD is plagued by mode mixing, which reduces the physical interpretability of the results. To mitigate this, Ensemble EMD (EEMD) was introduced, though it often leaves residual noise in the reconstruction. Subsequently, Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) was developed, achieving negligible reconstruction error and superior mode separation, thus providing a robust foundation for analyzing structural responses in noisy environments (Han et al., 2017; Ahmadi et al., 2025).

Nevertheless, a critical challenge in CEEMDAN based denoising is the reliable discrimination between signal dominant and noise dominant IMFs. Traditional criteria based solely on correlation coefficients or energy density often falter in complex noise environments where noise and vibration energy levels are comparable. To address this, this study proposes a CEEMDAN based denoising method incorporating a dual criterion of energy distribution and correlation. By calculating the instantaneous energy ratio of each IMF alongside its correlation coefficient with the original signal, a joint selection mechanism is established. This approach enables the adaptive identification of relevant components, suppressing noise while preserving structural dynamic information. Compared to conventional methods, the proposed dual criterion mechanism significantly reduces misclassification rates and enhances modal separation accuracy.

The remainder of this paper is organized as follows: Section 2 details the theoretical framework of the dual criterion CEEMDAN method; Section 3 evaluates performance via simulations and real-world datasets; and Section 4 concludes with a discussion of future research directions.

2. Proposed Methodology

Figure 1 illustrates the complete workflow of the proposed denoising algorithm for processing micro displacement signals of high-rise buildings acquired by ground based interferometric radar. The framework emphasizes the CEEMDAN based adaptive decomposition of radar signals and the dual criterion of energy and correlation for adaptive discrimination between effective signal components and noise.

This approach enables effective separation of multi frequency vibration sub signals and suppresses mode mixing, while accurately identifying the transition point between high frequency noise dominated IMFs and low frequency structure response dominated IMFs. As a result, the physical interpretability and frequency domain separability of modal components are significantly enhanced, providing a novel theoretical and methodological framework for denoising structural monitoring signals of high-rise buildings.

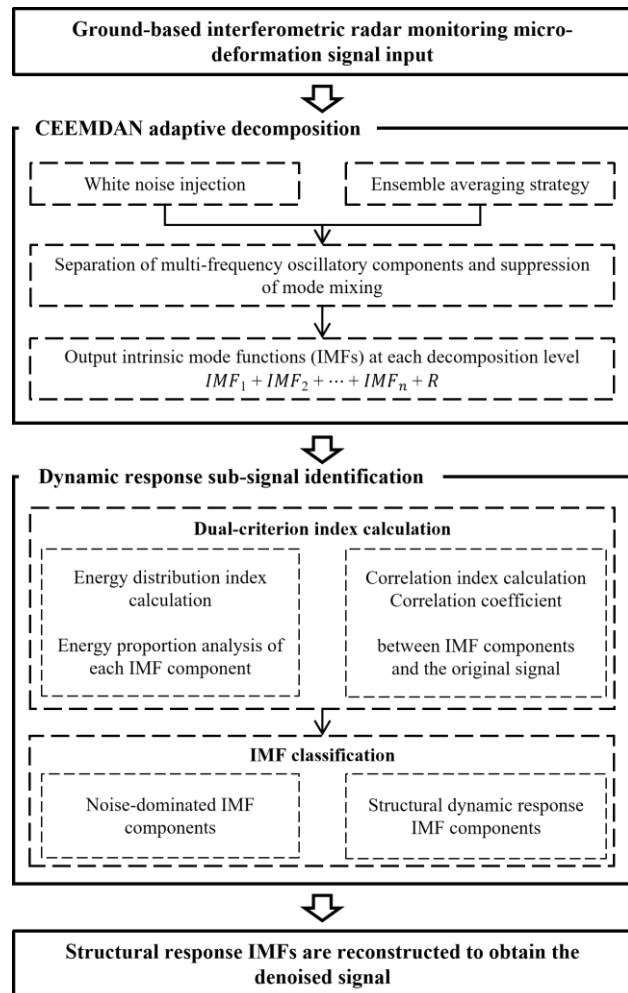


Figure 1. Workflow of the Proposed Method

2.1 Dual-criterion CEEMDAN denoising method

2.1.1 CEEMDAN adaptive decomposition

Empirical Mode Decomposition (EMD), proposed by Huang et al., is an adaptive time frequency analysis method designed for nonlinear and nonstationary signals. Its core idea is to decompose a complex signal into a set of intrinsic mode functions (IMFs) in a stepwise manner. Ultimately, the original signal can be expressed as the sum of all IMF components and a residual term, which can be written as:

$$x(t) = \sum_{i=1}^n c_i(t) + r_n(t) \quad (1)$$

However, the standard EMD suffers from a significant mode mixing problem. To address this issue, Wu and Huang proposed Ensemble Empirical Mode Decomposition (EEMD), which suppresses mode mixing by repeatedly adding Gaussian white noise and performing ensemble averaging of the decomposition results. Nevertheless, EEMD exhibits limitations in reconstruction completeness and relatively low computational efficiency.

To address these limitations, Torres et al. further proposed Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). The key improvement lies in the fact that, during the extraction of each IMF, adaptive white noise is injected directly into the current residual rather than the original signal. This strategy ensures the completeness and orthogonality of the decomposition. Let $E_k(\cdot)$ denote the EMD

operator used to extract the k -th order IMF, $\omega^m(t)$ be the standard Gaussian white noise in the m -th trial, ε_k be the adaptive noise amplitude coefficient at the k -th decomposition level, and M be the ensemble average number. The extraction of each IMF can then be expressed as:

$$IMF_1(t) = \frac{1}{M} \sum_{m=1}^M E_1(x(t) + \varepsilon_0 \omega^m(t)) \quad (2)$$

$$IMF_k(t) = \frac{1}{M} \sum_{m=1}^M E_k(r_{k-1}(t) + \varepsilon_{k-1} \omega^m(t)), k \geq 2 \quad (3)$$

where the residual at each decomposition level is recursively updated as $r_k(t) = r_{k-1}(t) - IMF_k(t)$. When $r_k(t)$ has no more than two extrema, the iteration is terminated. CEEMDAN guarantees strict reconstruction completeness, meaning that the original signal can be perfectly reconstructed from all decomposed components without error:

$$x(t) = \sum_{k=1}^n IMF_k(t) + r(t) \quad (4)$$

2.1.2 Adaptive denoising based on dual criteria of energy distribution and correlation analysis

CEEMDAN decomposes the original signal into a set of intrinsic mode function (IMF) components, where the energy carried by each IMF reflects the relative contribution of different frequency bands to the overall signal. For the i -th IMF component $IMF_i(t)$, its discrete time series is denoted as $\{c_k(n), n=1, 2, \dots, N\}$, where N is the total number of sampling points. The energy of the k -th IMF is defined as:

$$E_k = \sum_{n=1}^N c_k^2(n) \quad (5)$$

Then, the normalized energy ratio of the k -th IMF is defined to quantify the proportion of energy contributed by this component relative to the total energy of all decomposed modes, thereby describing its energy weight within the complete decomposition results, which can be written as:

$$ER_k = \frac{E_k}{\sum_{j=1}^n E_j + E_r} \quad (6)$$

where $E_r = \sum_{n=1}^N r^2(n)$ denotes the energy of the final residual component. The denominator represents the total energy of all IMF components and the residual term, ensuring the completeness of the normalization process. From a physical perspective, high frequency noise typically manifests as dense random fluctuations in the time domain, and its energy is mainly concentrated in high frequency IMF components, with relatively small energy differences among adjacent high order IMFs. In contrast, when the decomposition reaches the mid to low frequency range associated with the true structural dynamic response, the energy of the corresponding IMF components increases significantly. Therefore, the variation trend of ER_k with respect to the decomposition order k can serve as an important criterion for identifying the boundary between noise dominated and structural response dominated regions. Specifically, the difference between the normalized energy ratios of adjacent IMF orders is defined as:

$$\Delta ER_k = ER_{k+1} - ER_k \quad (7)$$

When ΔER_k transitions from a near zero steady state to a significant positive jump, it indicates that the $(k+1)$ -th IMF

begins to carry the dominant energy of the structural dynamic response. This position is therefore identified as a candidate boundary point indicated by the energy based criterion.

However, relying solely on energy distribution information is insufficient to fully distinguish between signal and noise. In particular, when the signal to noise ratio is low or the energy levels of signal and noise are comparable, the sensitivity of the energy based criterion may deteriorate. To address this limitation, a correlation based metric is introduced as a secondary criterion to evaluate each IMF from the perspective of waveform similarity. The Pearson correlation coefficient between the k -th IMF component $c_k(n)$ and the original noisy signal $x(n)$ is defined as:

$$\rho_k = \frac{\sum_{n=1}^N [c_k(n) - \bar{c}_k] [x(n) - \bar{x}]}{\sqrt{\sum_{n=1}^N [c_k(n) - \bar{c}_k]^2 \cdot \sum_{n=1}^N [x(n) - \bar{x}]^2}} \quad (8)$$

where $\bar{c}_k = \frac{1}{N} \sum_{n=1}^N c_k(n)$ and $\bar{x} = \frac{1}{N} \sum_{n=1}^N x(n)$ denote the mean values of the k -th IMF and the original signal, respectively. $\rho_k \in [-1, 1]$ represents the Pearson correlation coefficient. A larger absolute value of ρ_k indicates a stronger linear correlation between the IMF component and the original signal. From a physical perspective, low order IMFs dominated by high frequency noise exhibit almost no linear correlation with the original signal, and their $|\rho_k|$ values tend to approach zero. In contrast, mid to high order IMFs that contain the true structural vibration response preserve the dominant dynamic characteristics of the original signal and therefore show a much stronger correlation with it, resulting in significantly larger $|\rho_k|$ values. Consequently, the monotonic increasing trend of $|\rho_k|$ with respect to the decomposition order k serves as a second criterion for identifying the boundary point.

By integrating the energy distribution criterion and the correlation criterion, a dual criterion based joint rule is established to adaptively determine the boundary between noise dominant IMFs and structural response dominant IMFs. The decomposition order k^* is identified as the boundary point if and only if both conditions are simultaneously satisfied at the same order, that is:

$$k^* = \min \left\{ k \mid \Delta ER_k \geq \alpha \cdot \overline{\Delta ER} \text{ and } |\rho_{k+1}| \geq \beta \cdot |\rho_k| \right\} \quad (9)$$

where $\Delta ER_{k^*} = ER_{k^*+1} - ER_{k^*} \geq \alpha \cdot \overline{\Delta ER}$ and $\overline{\Delta ER} = \frac{1}{n-1} \sum_{k=1}^{n-1} |\Delta ER_k|$ denote the mean values of the energy difference sequence, and α is the energy jump sensitivity coefficient, typically set within $\alpha \in [2, 3]$, which controls the response threshold to energy variations. $|\rho_{k^*+1}| \geq \beta \cdot |\rho_{k^*}|$ represents the correlation based criterion, where β is the correlation jump coefficient, typically chosen within $\beta \in [1.5, 2.5]$. It requires a significant increase in the correlation coefficient between adjacent IMF orders, indicating

that the subsequent IMF begins to exhibit a substantial linear correlation with the original signal.

If the two criteria identify extrema at different decomposition orders, the more conservative position, namely the smaller order, is selected as the boundary point to ensure that noise components are sufficiently removed. The proposed dual criterion strategy evaluates the characteristics of each IMF from two independent perspectives, namely energy distribution and waveform similarity. This effectively overcomes the limitations of single criterion approaches under low signal to noise ratio conditions or energy overlap scenarios, and significantly improves the robustness and physical interpretability of boundary point identification.

2.2 Evaluation Index

To quantitatively evaluate the performance of the proposed denoising method, this study assesses the results from four perspectives, namely peak fidelity, noise suppression capability, signal distortion, and waveform similarity. Six statistical metrics are employed for a comprehensive evaluation, including the logarithmic relative error of peak value (LREPV), residual variance ratio (RVR), noise margin (NM), signal to error ratio (SER), Pearson correlation coefficient (PCC), and normalized cross correlation coefficient (NCC). The definitions and computational formulations of these metrics are described as follows.

2.2.1 Logarithmic Relative Error of Peak Value (LREPV)

LREPV is used to quantify the deviation of peak values between the denoised signal and the reference clean signal. It is defined as the base 10 logarithm of the ratio between the absolute peak error and the reference peak value. The formulation is given as:

$$LREPV = \log_{10} \left(\frac{|P_{denoised} - P_{clean}|}{|P_{clean}|} \right) \quad (10)$$

where $P_{denoised}$ denotes the peak value of the denoised signal, and P_{clean} represents the peak value of the reference clean signal. A smaller LREPV value indicates a higher degree of peak preservation after denoising, reflecting better fidelity of the seismic amplitude characteristics.

2.2.2 Noise Margin (NM)

NM expressed in decibels dB, measures the ratio between the effective signal energy after denoising and the residual error energy. It reflects the capability of the denoised signal to resist residual interference. The formulation is given as:

$$NM = 10 \log_{10} \left(\frac{\sum_n x_{clean}^2(n)}{\sum_n [x_{denoised}(n) - x_{clean}(n)]^2} \right) \quad (11)$$

A larger NM value indicates that the effective signal energy is significantly higher than the residual error energy, implying better denoising performance. In general, an NM value greater than 20 dB is considered to indicate satisfactory signal quality.

2.2.3 Signal to Error Ratio (SER)

SER expressed in decibels dB, directly quantifies the ratio between the energy of the reference clean signal and the error energy introduced during the denoising process, and is used to evaluate the degree of signal distortion. The formulation is given as:

$$SER = 10 \log_{10} \left(\frac{\sum_n x_{clean}^2(n)}{\sum_n e^2(n)} \right) \quad (12)$$

Where $e(n) = x_{denoised}(n) - x_{clean}(n)$ denotes the denoising error sequence. A larger SER value indicates lower waveform distortion introduced during the denoising process and thus higher denoising accuracy.

2.2.4 Pearson Correlation Coefficient (PCC)

PCC is used to quantify the linear correlation between the denoised signal and the reference clean signal, thereby evaluating waveform similarity from a statistical perspective. The formulation is given as:

$$PCC = \frac{\sum_n [x_{denoised}(n) - \bar{x}_d][x_{clean}(n) - \bar{x}_c]}{\sqrt{\sum_n [x_{denoised}(n) - \bar{x}_d]^2 \cdot \sum_n [x_{clean}(n) - \bar{x}_c]^2}} \quad (13)$$

Where $\bar{x}_d$ and $\bar{x}_c$ denote the mean values of the denoised signal and the reference clean signal, respectively. The PCC ranges from $[-1, 1]$. A PCC value approaching 1 indicates a high degree of waveform consistency between the denoised and reference signals, whereas a value close to 0 suggests weak linear correlation. Negative values imply an inverse correlation between the two signals.

2.2.5 Normalized cross Correlation Coefficient (NCC)

NCC is also employed to evaluate the waveform similarity between the denoised signal and the reference signal. Unlike PCC, NCC does not remove the mean value of the signals, making it more sensitive to the overall amplitude level and any direct current bias. The formulation is given as:

$$NCC = \frac{\sum_n x_{denoised}(n) \cdot x_{clean}(n)}{\sqrt{\sum_n x_{denoised}^2(n) \cdot \sum_n x_{clean}^2(n)}} \quad (14)$$

The NCC ranges from $[-1, 1]$, with values closer to 1 indicating better waveform matching between the denoised signal and the reference signal.

3. Experimental Results and Analysis

To verify the effectiveness of the proposed method, this study processes both simulated signals and micro deformation signals of the CCTV Tower acquired by ground based interferometric radar. A comprehensive evaluation is conducted in terms of signal decomposition, noise suppression, and signal reconstruction. In addition, the proposed method is compared with wavelet denoising and Kalman filtering methods.

3.1 Simulation Experiment

To quantitatively validate the effectiveness of the proposed CEEMDAN dual criterion denoising method, a simulated signal is constructed under controlled conditions with a known ground truth. By referencing the typical characteristics of displacement signals obtained from ground based radar monitoring of high rise buildings, the simulated signal is designed as a linear superposition of four components, namely structural harmonic response, impulse excitation, random excitation, and Gaussian white noise background. This design enables a systematic reproduction of the multi source mixed noise interference mechanisms observed in real monitoring scenarios.

The fundamental parameters of the simulated signal are set as follows: a sampling frequency of $f_s = 100\text{Hz}$, a signal duration of $T = 60\text{s}$, and a total number of sampling points $N = 6000$. The four signal components are expressed as:

$$\begin{cases} s(t) = \sum_{j=1}^3 A_j \sin(2\pi f_j t + \varphi_j) \\ v(t) = \sum_{p=1}^P B_p \cdot e^{-\xi_p(t-t_p)} \sin(2\pi f_v(t-t_p)) \cdot u(t-t_p) \\ w(t) = \mathcal{F}^{-1} \left\{ \sqrt{S_w(f)} \cdot \Phi(f) \right\} \\ n(t) \sim \mathcal{N}(0, \sigma_n^2) \end{cases} \quad (15)$$

To evaluate the denoising performance of the proposed method, EMD based threshold denoising and EEMD based threshold denoising are selected as comparative approaches (Figure.2). All three methods are applied to the same simulated signal, and the results are illustrated in the figure. It can be clearly observed that the reconstructed signal obtained by the proposed CEEMDAN dual criterion method (red solid line) exhibits the highest level of agreement with the clean signal (blue dashed line) in terms of waveform shape, amplitude, and phase consistency. The positions of peaks and troughs closely match those of the clean signal, and both the overall trend and fine scale features are well preserved.

In contrast, the reconstructed signal from the EEMD thresholding method (red) retains the main low frequency trend, but fails to fully suppress high frequency oscillations. Noticeable random deviations from the clean signal remain, and the waveform exhibits evident fluctuations. The EMD thresholding method (green) shows a similar incomplete denoising effect, with residual noise present in certain time intervals. In particular, significant deviations are observed near zero crossing points, and the overall agreement with the reference signal is inferior to that achieved by the proposed method.

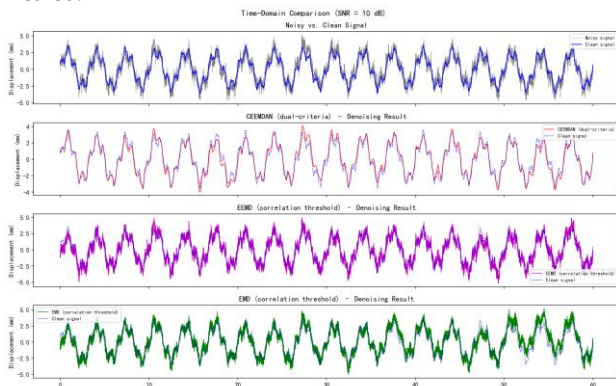


Figure 2. Comparison of Denoising Results from Three Methods

Figure 3 presents a comparison of the power spectral density of the three methods within the frequency range of 0–20 Hz. The clean signal (blue) exhibits three distinct sharp spectral peaks at 0.30 Hz, 1.25 Hz, and 3.60 Hz, corresponding to the structural resonance frequencies, while the energy in other frequency bands is negligible, with a background noise level on the order of 10^{-32} . The noisy signal (gray) shows a relatively uniform noise floor across the entire frequency range. The proposed CEEMDAN dual criterion method (red) accurately restores both the positions and amplitudes of the three spectral peaks within

the structural vibration band of 0–5 Hz. Meanwhile, the high frequency noise above 5 Hz is significantly suppressed, with the spectral floor decreasing monotonically with increasing frequency and reaching approximately 10^{-9} at around 15 Hz, demonstrating excellent broadband noise suppression capability.

In contrast, the EEMD thresholding method (magenta dashed line) and the EMD thresholding method (green dash dotted line) fail to effectively reduce high frequency noise. Their power spectral densities remain close to that of the noisy signal, maintaining a noise level on the order of 10^{-4} within the 5–20 Hz range, indicating limited effectiveness in suppressing high frequency noise.

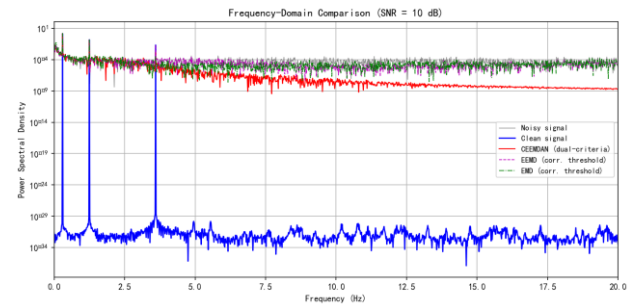


Figure 3. Comparison of Power Spectral Density of the Three Methods in the 0–20 Hz Frequency Range

Table 1 presents the mean values and standard deviations of the evaluation metrics for the three denoising methods. From the perspective of standard deviation, the proposed method consistently exhibits significantly lower variability than both EEMD and EMD methods under all conditions. For instance, the standard deviation of PCC for the proposed method is 0.001, whereas those of EEMD and EMD are 0.026 and 0.042, respectively, representing a reduction by approximately 26 to 42 times. This indicates that the dual criterion based identification strategy, which constrains the boundary point from two independent dimensions of energy distribution and correlation, effectively avoids misclassification caused by noise specific characteristics in single criterion approaches, thereby enhancing the repeatability and robustness of the denoising results.

Table 1. Results of Evaluation Metrics

	LREPV	RVR	NM	PCC	dSNR
Proposed Method	-0.8612	0.4056	12.2470	0.9716	3.9195
EEMD	-0.2248	1.3422	7.2509	0.9142	-1.0767
EMD	-0.2637	1.4947	6.9701	0.9033	-1.3575

The simulation results demonstrate that the proposed CEEMDAN based adaptive denoising method with a dual criterion outperforms both EEMD thresholding and EMD thresholding methods in terms of signal to noise ratio improvement, waveform fidelity, noise suppression effectiveness, and result stability. These findings comprehensively validate the effectiveness and robustness of the proposed approach.

3.2 Practical Experiment

The CCTV Tower is located in Haidian District, Beijing, with a total height of 405 m. To achieve high precision continuous displacement monitoring, an IBIS S radar system was employed in this experiment. The system was installed on a concrete plaza approximately 240 m east of the tower to avoid potential

measurement errors caused by ground subsidence. The detailed instrument configuration is illustrated in Figure 4. The monitoring experiment was conducted on July 7, 2023, from 15:00 to 16:00. The radar system operated with a sampling frequency of 60.95 Hz, a maximum range resolution of 0.75 m, a maximum observation distance of 500 m, and an elevation angle of 52.5°.



Figure 4. IBIS-S radar system emplacement locations

Experimental validation was conducted using micro-deformation data of the Central Television Tower acquired by the IBIS-S radar system. The proposed method, along with wavelet denoising and Kalman filtering, was applied for noise processing. A comparative analysis of the results, as summarized in Figure 5 and Table 2, demonstrates the superior performance of the proposed method across multiple metrics. It achieved the lowest Noise Module (NM, 0.0212), the highest Pearson correlation coefficient (0.9985), and the highest Normalized Cross-Correlation (NCC, 15758.82). In addition, both the root variance ratio and signal energy ratio were close to 1.

These outcomes indicate that the proposed method not only effectively suppresses noise in high-rise structure monitoring but also preserves essential features of the original signal—including waveform shape, trend, peak amplitude, and energy distribution—to a remarkable extent. The method exhibits the highest waveform similarity and superior peak retention capability, with energy distribution and fluctuation characteristics nearly identical to those of the original signal. In contrast, wavelet denoising tends to attenuate peaks and lose subtle details, while Kalman filtering often leads to over-smoothing and consequent signal distortion.

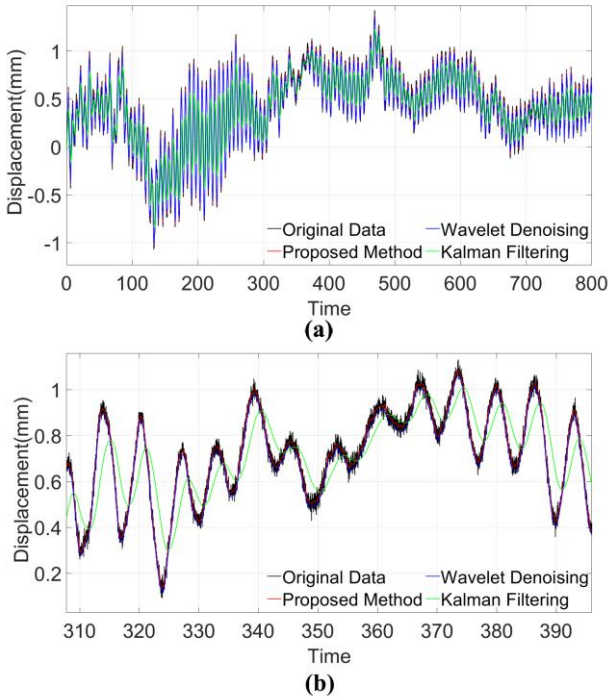


Figure 5. Denoising Results of Time Series Using Wavelet Denoising, Kalman Filtering, and the Proposed Method

Table 2. Results of six evaluation metrics in the practical experiment

	LREPV	RVR	NM	SER	PCC	NCC
Proposed Method	0.0668	0.9985	0.0212	0.9993	0.9985	15758.8
Wavelet Denoising	0.0868	0.9754	0.0283	0.9708	0.9982	15305.2
Kalman Filtering	0.4726	0.8596	0.1980	0.9359	0.8606	12992.3

As shown in Figure 6, all denoising methods successfully identified the peaks at the dominant frequencies of the signal. Within the structural frequency range of 0.1 – 5 Hz, the proposed method maintained the amplitude of peaks while significantly suppressing high-frequency noise floor, resulting in the sharpest peaks and the highest frequency resolution. In contrast, the Kalman filter exhibited a certain degree of over-smoothing, leading to reduced peak amplitudes. In the high-frequency noise region of 5– 20 Hz, the proposed method also demonstrated superior noise suppression capability. Comprehensive analysis confirms that the proposed method offers clear advantages in peak preservation, high-frequency noise suppression, and discrimination of closely spaced frequency components.

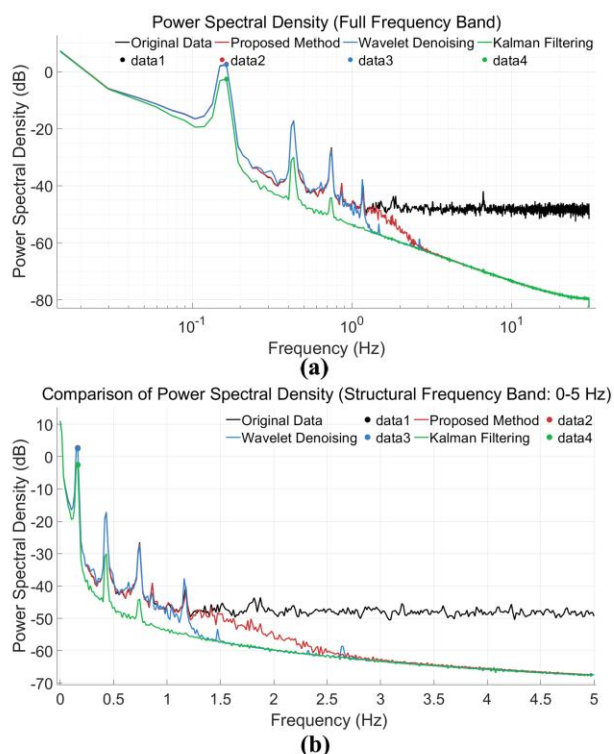


Figure 6. Power Spectral Density Comparison of Three Denoising Methods

As shown in Figure 7, residual analysis demonstrates the superior performance of the proposed method. Its residual amplitude is the smallest and fluctuates most stably around zero, while removing the least amount of noise, indicating optimal preservation of the true structural signal. Statistically, the probability distribution curve of the residuals after denoising by the proposed method is the steepest with the highest peak, reflecting greater stability and consistency in the denoising process. Autocorrelation function analysis reveals that the residuals of the proposed method decay most rapidly and most closely resemble white noise, further confirming the thoroughness of its denoising effect. In the frequency domain, all methods exhibit high residual power spectral density above 10 Hz, consistent with the noisedominant nature of this frequency range. Within the main structural vibration band of 0.5–5 Hz, the proposed method removes the least amount of valid signal components, thereby maximally preserving the true structural response.

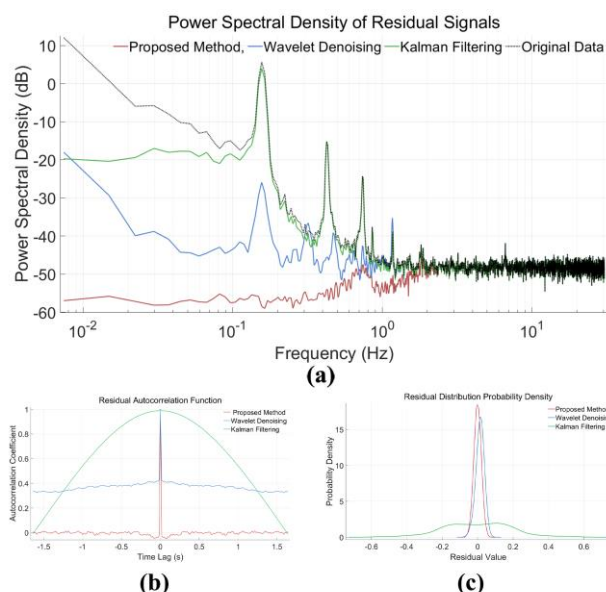


Figure 7. Residual Analysis Results from Three Denoising Methods

4. Conclusions

This study addresses the critical challenge of nonstationary mixed noise interference in monitoring high rise structures using ground based interferometric radar. A fully adaptive denoising method is proposed based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) combined with a dual criterion of energy and correlation, and its performance is systematically validated through both simulation experiments and real world measurements. The proposed CEEMDAN based dual criterion adaptive denoising method demonstrates strong performance under both simulated and practical conditions in terms of denoising accuracy, signal fidelity, noise suppression effectiveness, and result stability. It is particularly well suited for processing nonstationary and nonlinear displacement signals in ground based interferometric radar based structural health monitoring of high-rise buildings, and provides a reliable methodological foundation for accurate identification of structural dynamic parameters and micro deformation extraction. Future work will focus on extending the proposed framework to real time processing scenarios and exploring its applicability to other types of dynamic structural monitoring platforms.

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