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CEEMD-UNet: Feature-Preserving Deep-Denoising Method for High-rate GNSS coseismic displacement

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Abstract

High-rate Global Navigation Satellite System (GNSS) observations provide direct measurements of surface coseismic displacements and are a key tool for seismic monitoring. However, the signal-to-noise ratio (SNR) of high-rate GNSS coseismic displacement data is often low in the case of moderate-magnitude or distant earthquakes, and traditional denoising methods struggle to balance noise suppression with signal preservation. To overcome this problem, this study proposes a new feature-preserving deep-denoising method based on complementary ensemble empirical mode decomposition (CEEMD) and UNet network (CEEMD-UNet). The proposed method first adaptively decomposes the non-stationary coseismic displacement via CEEMD, effectively overcoming the limitations of conventional denoising techniques. The resulting intrinsic mode functions (IMFs) are then accurately denoised using a UNet network, achieving an effective balance between noise removal and preservation of coseismic signal features. Tests on synthetic data show that after denoising, the average cross-correlation coefficients in the E, N, and U directions all exceed 0.85, and the average SNR is improved by factors of 14.72, 12.84, and 38.77, respectively. Validation using real GNSS data from the 2018 Mw 7.0 Anchorage, Alaska earthquake indicates that the average root mean square error across stations is reduced by 41.39%, 48.79%, and 67.90% in the three components, while the SNR is increased by factors of 5.05, 2.89, and 0.96. Compared with CEEMD-WD and UNet-only denoising methods, the proposed approach demonstrates significant advantages in waveform consistency,

amplitude preservation, and cross-scenario adaptability, offering a reliable technical solution for processing low-SNR high-rate GNSS seismic data.

Keywords: High-rate GNSS; denosing; CEEMD; Deep learning; Convolutional Neural Network

1. Introduction

Over the past two decades, high-rate Global Navigation Satellite System (HR-GNSS) has enabled the real-time capture of instantaneous, large-scale surface deformations. It compensates for the amplitude saturation limitation that is prevalent in conventional seismometers during strong earthquakes, thereby greatly advancing the development of large-scale seismological research (Larson KM 2009; Xu C et al. 2016). This progress is evidenced by its increasingly widespread applications in such fields as the real-time monitoring of seismic coseismic deformation and the rapid inversion of seismic source parameters (Birinci S et al. 2024; Jia Z et al. 2025; Li X et al. 2019). However, coseismic displacements derived from HR-GNSS suffer from low signal-to-noise ratio (SNR), which poses significant challenges to the high-precision inversion of seismic source parameters and dynamic monitoring of coseismic deformations (Geng et al., 2018; Melgar et al., 2020). Consequently, improving accuracy of HR-GNSS displacements has become an essential preprocessing step in HR-GNSS seismological applications.

The current mainstream HR-GNSS denoising methods can be broadly classified into physics-model-driven methods and data-driven methods. Physics-model-driven methods are founded on the physical mechanisms and laws of GNSS observation errors, to develop targeted models for mitigating specific noise sources (Zhang X et al. 2025). Nevertheless, these methods suffer from narrow applicability, high model complexity, and strong prior-information reliance, which cannot effectively handle complex composite noise (Dong D et al. 2016; Wang Z et al. 2020). In contrast, data-driven methods are not dependent on the physical mechanisms underlying GNSS observation errors; instead, they achieve the separation of noise from effective signals through mathematical transformations or statistical analyses of the data. Yet, they are afflicted

by signal distortion risk, strong parameter dependence, and limited generalization capability (Costantino G et al. 2024; Thomas A et al. 2023; Wnęk A and Kudas D 2025). Despite notable advancements, related research efforts still confront numerous challenges. Specifically, small amplitudes of station displacement often induce frequency overlap between GNSS seismic waves and noise, thereby increasing the complexity of denoising workflows.

To address these challenges, this paper presents a feature-preserving deep-denoising method based on Complete Ensemble Empirical Mode Decomposition and U-Net Convolutional Neural Network (CEEMD-UNet) for high-rate GNSS coseismic signals. Our methodology advances the field through three principal innovations:

- A hybrid denoising framework combining CEEMD method and UNet model is proposed. Through CEEMD preprocessing, non-stationary HR-GNSS seismic signals are decomposed into multiple Intrinsic Mode Function (IMF) components, which essentially eliminates mode mixing problem and provides input data with distinct features for subsequent deep learning-based denoising.
- A component-wise deep learning denoising strategy is designed. Utilizing strengths of UNet model in nonlinear feature extraction, targeted denoising is performed on each IMF component, which significantly enhances the capability of preserving waveform amplitude features and improves the quality of signal reconstruction under low signal-to-noise ratio (SNR) conditions.
- The performance of the UNet model is enhanced using the CEEMD decomposition mechanism. This effectively mitigates the over-denoising defect of a single deep learning model in the vertical direction, reduces the algorithm performance degradation in low SNR scenarios, and achieves the synergistic improvement of co-seismic feature preservation and denoising accuracy.

The remainder of this paper is organized as follows: Section 2 provides a comprehensive review of data-driven denoising methods. Section 3 details the methodology of the proposed CEEMD-UNet method. In Section 4, systematic experiments are conducted on synthetic datasets to validate the proposed denoising method. Section 5 carries out a comparative evaluation and result analysis between the

proposed method and three other mainstream methods using real HR-GNSS coseismic dataset. Finally, Section 6 summarizes the entire paper and outlines future research directions.

2. Related works

On the basis of core principles and technical frameworks, the dominant data-driven methods for improving accuracy of HR-GNSS data can be classified into four types: spatiotemporal filtering methods, signal decomposition methods, machine learning (ML) and deep learning (DL) methods, and hybrid combined methods.

Spatiotemporal filtering methods suppress noise by utilizing the spatial and temporal correlations of multi-station GNSS data. Their core principle is to construct a regional reference network to separate and eliminate spatially correlated common-mode errors (CMEs) (e.g., tropospheric delay, satellite orbit error, clock error) and station-specific errors (e.g., multipath error, observation noise) embedded in single-station observations. The primary methods include sidereal filtering (SF) (Genrich JF and Bock Y 1992), stacking filtering (STK) (Wdowinski S et al. 1997), principal component analysis (PCA) (Dong D et al. 2006) and their improved variants (Atkins C and Ziebart M 2016; Ji K et al. 2023; Zhong P et al. 2010). These methods effectively isolate errors, induce minimal distortion to valid signals, offer clear physical interpretability, and require no predefined models, making them particularly suitable for deformation monitoring with dense station networks (He X et al. 2015). Nevertheless, these methods have distinct limitations: they are highly dependent on station density and yield poor performance in sparse networks; when significant heterogeneous deformation occurs within the target region, real deformation signals may be misidentified as common-mode errors and thus removed (Li W et al. 2022; Tian Y and Shen Z-K 2016). When significant heterogeneous deformation occurs within the target region, real deformation signals may be misidentified as common-mode errors and thus removed. In addition, their applicability is constrained by nonlinear and non-stationary coseismic deformation signals, with a tendency to discard fine-grained signal details (Li Yanyan et al. 2021). For SF method, if the frequency components of

coseismic signals overlap with the sidereal day band, the filtering process is prone to distorting valid signals (Geng J et al. 2018). Meanwhile, as the algorithm relies on high-precision spectrum analysis, its performance is limited when processing short-time-series coseismic displacement data (Li Y et al. 2019).

Signal decomposition methods operate on the core principle of adaptively decomposing GNSS signals into sub-signals of distinct frequency bands using time-frequency localization techniques, followed by noise separation via thresholding or component screening. The primary approaches include wavelet denoising (WD) (Donoho DL 1995), empirical mode decomposition (EMD) (Huang NE et al. 1998), variational mode decomposition (VMD) (Dragomiretskiy K and Zosso D 2014) and their improved variants (Pan Z et al. 2025; Zhengkai H et al. 2023). These methods offer prominent advantages: they excel at processing nonlinear and non-stationary signals, boast strong adaptability and superior time-frequency localization characteristics, rendering them particularly suitable for mitigating multipath effects and random noise in GNSS data (Wang Z and He X 2025; Wnęk A and Kudas D 2025; Xu H et al. 2021). Nevertheless, they exhibit their respective distinct limitations. The denoising performance of wavelet transform is highly sensitive to wavelet mother function selection, and its lack of inherent adaptability to dynamic signal characteristics limits its performance in non-stationary scenarios.(Lau L 2017). EMD is susceptible to mode mixing and faces challenges in establishing objective thresholds for separating signal and noise components during reconstruction, thereby affecting the robustness of the denoised output (Wu Z et al. 2009). To address the issue of the mode mixing, several advanced variants of EMD have been developed: ensemble EMD (EEMD) (Wu Z and Huang NE 2009), complete ensemble EMD (CEEMD) (Yeh JR et al. 2010) and other related methods(Huang S et al. 2019; Li Y et al. 2018b; Pan Z et al. 2025). Comparative analyses indicate that CEEMD offers superior computational efficiency relative to EEMD. Furthermore, CEEMD demonstrates enhanced efficacy in mitigating residual noise introduced by auxiliary white-noise injections during the decomposition process (Calvo MS and Lee HS 2024). VMD simplifies the mode decomposition process and exhibits excellent separation performance. Nevertheless, the VMD method still requires

careful selection of key parameters; inappropriate parameter settings can lead to mode mixing or spurious modes, thereby compromising the signal decomposition performance (Peng Z et al. 2025).

ML and DL methods are fundamentally based on data-driven models that learn complex mapping relationships between noise and valid signals, utilizing neural networks to automatically extract features and achieve end-to-end denoising. Recent advances in signal processing increasingly demonstrate that such methods, including convolutional neural network (CNN) (Quinteros-Cartaya C et al. 2024) and autoencoder (AE) (Saad OM et al. 2021), exhibit remarkable advantages in advancing seismological and crustal deformation research (Dalai B and Kumar P 2025; Kubo H et al. 2024; Mousavi SM and Beroza GC 2022; Thomas AM et al. 2021; Zhang C and Baan Mvd 2020). These methods also exhibit notable limitations, such as requiring a substantial amount of annotated data for training, limited model interpretability, high computational resource consumption during the training process, and model performance that is highly dependent on the quality and distribution of the training data, resulting in constrained generalization ability under conditions of data scarcity or distribution mismatch (Jia K and Zhou S 2024; Kubo H et al. 2024; Mousavi SM and Beroza GC 2023). However, they possess the capability to automatically learn signal features without the need for manual filter parameter design, demonstrate robust modeling capacity for complex nonlinear noise. As a key DL architecture, CNN have been effectively applied to seismic record denoising by leveraging their strong feature extraction and representation learning capabilities to autonomously retrieve diagnostic information from multi-dimensional data (Ende Mvd et al. 2023; Thomas A et al. 2023; Zhang C and Baan Mvd 2020). For example, Zhu W et al. (2019) developed a novel denoising algorithm named DeepDenoiser engineered to enhance earthquake detection capabilities through an advanced deep neural network architecture. This framework is designed to perform simultaneous learning of a sparse time-frequency representation from input data and a nonlinear mapping function that generate adaptive masks for precise signal-noise separation. However, as DeepDenoiser was originally designed only for single-channel seismic data processing, Thomas A et al. (2023) introduced

structural adaptations to the model to enable its application to three-component high-rate GNSS data. Three modified versions of DeepDenoiser were subsequently evaluated, which to some extent alleviated issues of amplitude distortion and phase deviation in the denoised outputs.

Hybrid combined methods integrate the technical strengths of two or more individual approaches to construct multi-stage, multi-level denoising frameworks, thereby compensating for the limitations of single methods. Typical examples mainly include WD-CEEMD (Wnęk A and Kudas D 2025), CEEMD-multiscale multiway PCA(Li Y et al. 2018a) , WD-CNN hybrid models (Carbonari R et al. 2023) and other hybrid variants (Yang X et al. 2025; Yu L et al. 2024). These approaches suffer from high algorithmic complexity and considerable difficulty in coordinating parameters across multiple integrated methods. However, their advantages lie in their ability to leverage the respective merits of different techniques, significantly enhancing denoising performance in complex scenarios (Li Y et al. 2017; Zhengkai H et al. 2023).

3. Methodology

3.1 CEEMD method

CEEMD, as a modified variant of EMD, serves as an adaptive analytical tool for nonlinear and non-stationary time series (Huang NE et al. 1998), which can effectively mitigate mode mixing, which is a prominent limitation of the original EMD. This method enables the adaptive decomposition of a target time series into a finite set of IMFs according to the inherent characteristics of the original signal.

A core procedure of CEEMD involves the addition and subsequent cancellation of White Noise (WN) to and from the input data (Yeh JR et al. 2010). The target signal S_d to the CEEMD algorithm is defined as follows:

$$S_d = \sum_{i=1}^P IMF_{i_d} + R \quad (1)$$

where IMF_{i_d} denotes the i -th IMF component for direction d (east, north or vertical) of HR-GNSS coseismic signals, and R represents the last IMF as a residue.

3.2 U-Net model architecture

U-Net, a classic and highly influential CNN architecture, primarily consists of an encoder (down-sampling path) and a decoder (up-sampling path). Based on the U-Net architecture, Zhu W et al. (2019) proposed the deep denoising method (DeepDenoiser), in which a noisy signal $G(t)$ is defined as the linear superposition of a known true signal $S(t)$ and known noise $N(t)$, i.e.:

$$G(t) = S(t) + N(t) \quad (2)$$

In the frequency domain, the STFT of the noisy signal, denoted as $G(t, f)$, is expressed as the linear superposition of the STFT of the underlying the clean signal $S(t, f)$ and the STFT of the additive noise component $N(t, f)$:

$$G(t, f) = S(t, f) + N(t, f) \quad (3)$$

Then, the signal mask $M_S(t, f)$ and noise mask $M_N(t, f)$ are respectively defined as:

$$M_S(t, f) = \frac{I}{I + \frac{|N(t, f)|}{|S(t, f)|}}; \quad M_N(t, f) = \frac{\frac{|N(t, f)|}{|S(t, f)|}}{I + \frac{|N(t, f)|}{|S(t, f)|}} \quad (4)$$

Each mask takes values in the range $[0, 1]$, and maintains the same dimensionality as the input STFTs. During training, the model outputs the estimated signal mask $\hat{M}_S(t, f)$ and noise mask $\hat{M}_N(t, f)$. Therefore, the predicted clean signal $\hat{S}(t)$ and the separated noise component $\hat{N}(t)$ are derived by multiplying $G(t, f)$ with their respective masks, followed by the application of the inverse STFT:

$$\hat{S}(t) = STFT^{-1} \{ G(t, f) \hat{M}_S(t, f) \} \quad (5)$$

$$\hat{N}(t) = STFT^{-1} \{ G(t, f) \hat{M}_N(t, f) \} \quad (6)$$

Thomas A et al. (2023) proposed three improved models based on DeepDenoiser (Zhu W et al. 2019), denoted as Model 1, Model 2, and Model 3, respectively. Among them, Model 1 primarily increases the number of network channels but employs a real-valued mask, which does not account for the phase difference between the signal and noise, potentially leading to amplitude distortion in the reconstructed signal. To address

this, Model 2 employs a linear activation function in the output layer to directly predict the real and imaginary parts of the complex-valued $S(t, f)$ normalized by the maximum absolute value of $G(t, f)$. In order to simultaneously represent phase differences and minimize amplitude distortion, Model 3 directly predicts the ratio $S(t, f)/G(t, f)$. The research results of Thomas A et al. (2023) indicate that Model 2 outperforms both Model 1 and Model 3 across the full signal-to-noise ratio range. Therefore, the architecture of Model 2 is adopted for model training in this study.

3.3 Architecture of CEEMD-UNet model

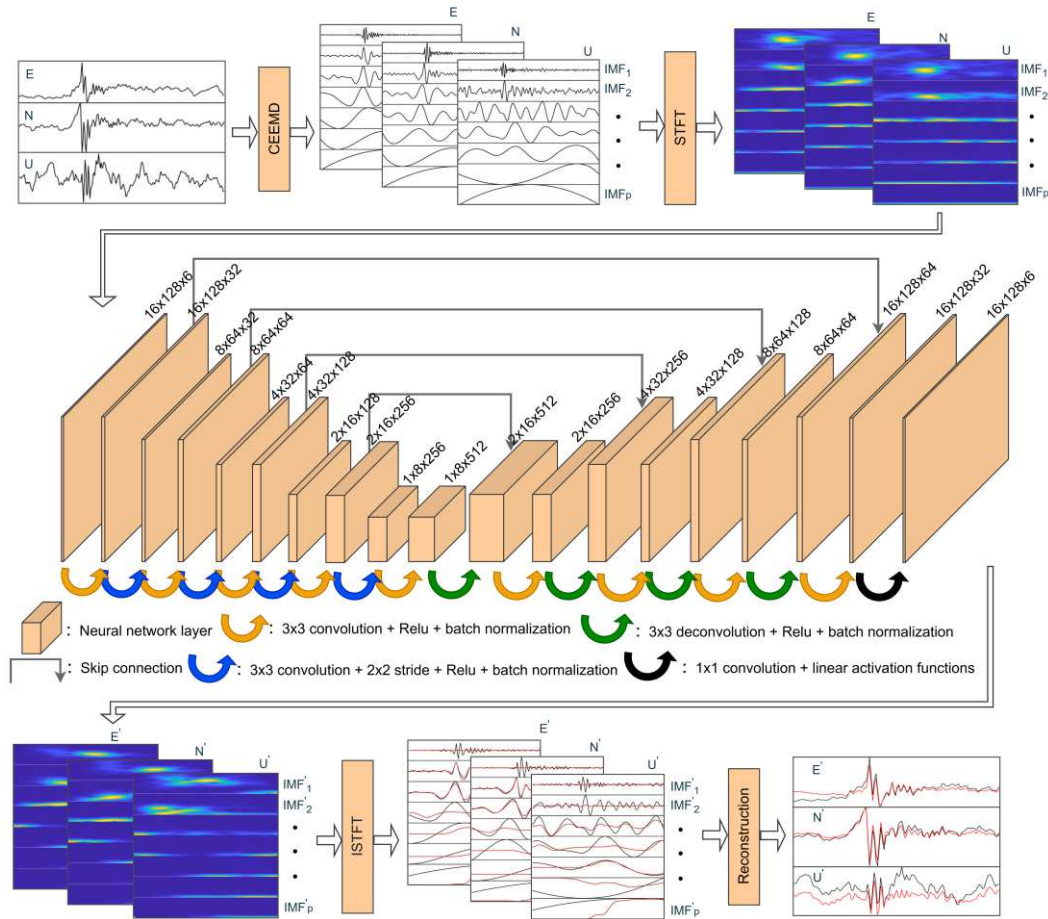


Fig. 1 Flowchart of the proposed CEEMD-UNet denoising method.

The overall architecture of the CEEMD-UNet denoising method is illustrated in Figure1. First, the proposed approach employs CEEMD for the original high-rate GNSS seismic waveform, decomposing complex non-stationary signals into a series of Intrinsic Mode Functions (IMFs) according to Equation (1). For the east (E), north (N),

and vertical (U) directions, the corresponding IMFs are denoted as IMF_{P_E} , IMF_{P_N} and IMF_{P_U} , respectively. Subsequently, the IMF components of the same order from the three directions are combined to form three-component input data. The Short-Time Fourier Transform (STFT) is then applied to convert the three-component data into the time-frequency domain, and the real and imaginary parts of the resulting time-frequency coefficients are processed by a U-Net network for perform denoising, yielding refined estimates of both the real and imaginary parts.

As shown in Figure 1, the network architecture of U-Net is designed in the form of a series of fully convolutional layers. The dimension information above each layer indicates “frequency bins $\times$ time points $\times$ channel numbers”. The size of the feature maps first decreases and then increases, and skip connections are employed to enhance training convergence speed and prediction performance. The input to the first layer consists of the real and imaginary parts of the time-frequency coefficients of the data $G(t, f)$. The input time-frequency coefficients are processed and transformed through a series of two-dimensional convolutional layers, which incorporate rectified linear unit (ReLU) activation layers and batch normalization (Ioffe S and Szegedy C 2015). The convolution filter size remains constant (3×3), but in the first part of the network, a stride of 2×2 is used to progressively reduce the feature-space dimensions through down-sampling. In the latter part of the network, deconvolution (the transpose of a convolutional layer) is applied for up-sampling. In the final layer, a linear activation function is adopted to predict the real and imaginary parts of the complex value $S(t, f)$.

The denoised time-frequency representations are subsequently converted back to the time domain using the Inverse STFT to obtain the cleaned IMFs, which are denoted as IMF'_{P_E} , IMF'_{P_N} and IMF'_{P_U} , respectively. Finally, signal reconstruction is carried out to produce the denoised output. The reconstruction formula is expressed as follows:

$$S'_d = \sum_{i=1}^P IMF'_{i_d} \quad (7)$$

where S'_d represents the final denoised signals for the East, North, and Vertical

components, respectively, processed by the proposed method. This integrated strategy mitigates performance degradation and over-denoising under low signal-to-noise ratio conditions, thereby enhancing both the effectiveness and practical applicability of denoising for high-rate GNSS seismic signals.

3.4 Model training

This study employs the synthetic high-rate GNSS database published by Lin J-T et al. (2020) for model training. This database is constructed based on the Chile subduction zone and contains simulated station records for 36,800 rupture scenarios (Fig.2). The earthquake epicenters cover an area of approximately 600,000 km², with a magnitude range from Mw 6.6 to Mw 9.6 and a maximum focal depth of 55 km.

The model was trained for 50 epochs using the TensorFlow framework (Abadi M et al. 2016). The dataset was split into training and validation sets in a 9:1 ratio. The validation set did not participate in the model training process and was solely used for rapid assessment of the training performance. The Adam optimization algorithm (Kingma DP and Ba JJC 2014) was adopted for network training, with the learning rate set to 0.0001 and a dropout rate of 0.2%.

The accuracy of the model was evaluated using the mean squared error (MSE) loss function (Fig.3). Figure 3 illustrates the variation curve of the loss function during the training process. The blue solid line represents the training loss, while the red dashed line denotes the validation loss. Overall, the training residual and the validation residual are largely consistent, indicating that the model exhibits excellent convergence behavior and generalization capability.

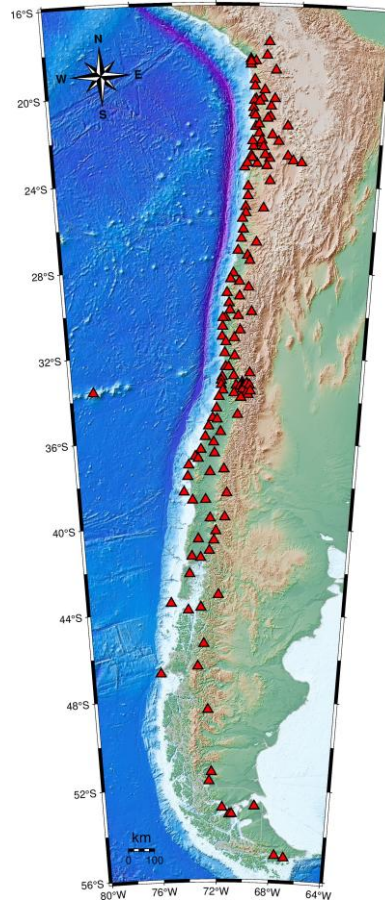


Fig. 2 Distribution of GNSS stations in the Chile subduction zone. The red triangles in the figure represent the GNSS stations.

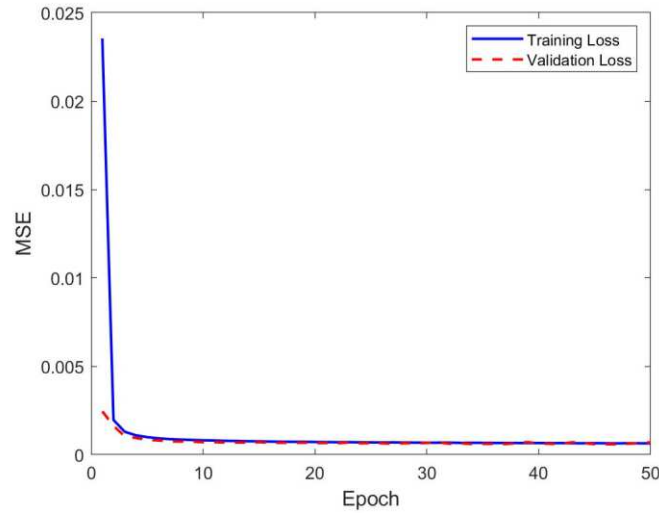


Fig. 3 Variation curves of model training residual and validation residual.

3.5 Performance evaluation metrics

To comprehensively evaluate the effectiveness of the denoising method proposed in this study, three different quantitative metrics are employed for systematic analysis,

covering signal similarity, noise consistency, and spatial distance measures.

(1) Normalized cross-correlation (NCC)

NCC is used to quantify the waveform similarity between the denoised signal and the true signal, defined as follows:

$$NCC = \frac{1}{n} \sum_{x,y} \frac{1}{\sigma_f \sigma_t} (f(x,y) - \mu_f)(t(x,y) - \mu_t) \quad (8)$$

where n represents the window size; $f(x,y)$ and $t(x,y)$ denote the two signal samples under comparison; σ_f and σ_t are the standard deviations of $f(x,y)$ and $t(x,y)$, respectively; and μ_f and μ_t are the means of $f(x,y)$ and $t(x,y)$, respectively.

The value of NCC ranges from $[-1,1]$: a value of 1 indicates perfect positive correlation between the two signals, a value of -1 indicates perfect negative correlation, and a value close to 0 indicates no significant correlation.

(2) Signal-to-noise ratio (SNR)

SNR is used to evaluate the energy ratio between the effective signal component and the noise component, calculated as:

$$SNR = \frac{\max(|s|)}{2 * \sigma_n} \quad (9)$$

where $\max(|s|)$ denotes the absolute maximum value of the signal, and σ_n is the standard deviation of the noise in the pre-arrival background window of the P-wave. An $SNR \approx 1$ indicates that the signal and noise energies are comparable; $SNR > 1$ implies that the signal dominates; if the noise standard deviation approaches zero, the SNR tends toward infinity. For the test dataset, SNR values are calculated before and after denoising, and the change ΔSNR is further analyzed to reflect the improvement in denoising performance.

(3) Euclidean distance (ED)

Euclidean distance is used to measure the difference between the true signal and the noisy/denoised signals, defined as:

$$D^2(m,n) = \sqrt{\sum_i (m_i - n_i)^2} \quad (10)$$

where m and n represent the vectors corresponding to the two signal sets, and m_i and n_i denote all components of the respective vectors. A smaller value indicates that the denoising result is closer to the true signal in both amplitude and waveform morphology.

4 Performance evaluation on the test dataset

4.1 Denoising results

To assess the adaptability of the proposed method under different SNR conditions, Figures 4–6 demonstrate its denoising performance on several typical synthetic datasets. These test examples span from low to relatively high SNR values, covering challenges from single-directional signal degradation to multi-directional composite scenarios. This comprehensive test can verify the robustness and effectiveness of the proposed method.

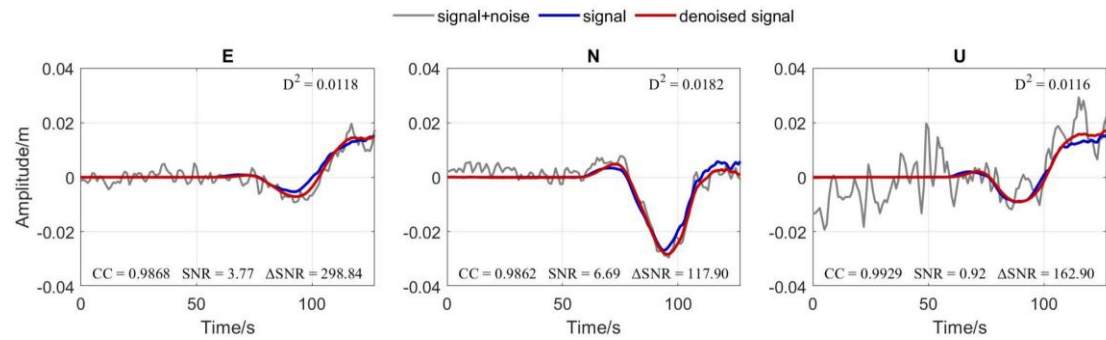


Fig. 4. Denoising results on the test dataset (low SNR in the U direction,). CC represents the cross-correlation coefficient between the true signal and the denoised signal; SNR is the signal-to-noise ratio of the noisy signal; ΔSNR denotes the change in SNR after denoising; and D^2 is the distance between the true signal and the denoised signal.

Figure 4 displays a test case with a relatively low SNR value of 0.92 in the U-direction, while the SNR values in the E and N directions are relatively high at 3.77 and 6.69, respectively. After applying the proposed denoising model, the CC values between the denoised waveforms and the true signals reach 0.99 in all three directions, indicating a high temporal similarity between the denoised and original signals. Moreover, the SNR values are significantly enhanced by factors of 79.27, 17.62, and 177.07 in the E, N, and U directions, respectively. These results demonstrate that the robustness and effectiveness of the proposed method in noise suppression and signal

recovery, even under the challenging condition of a low SNR in the vertical direction.

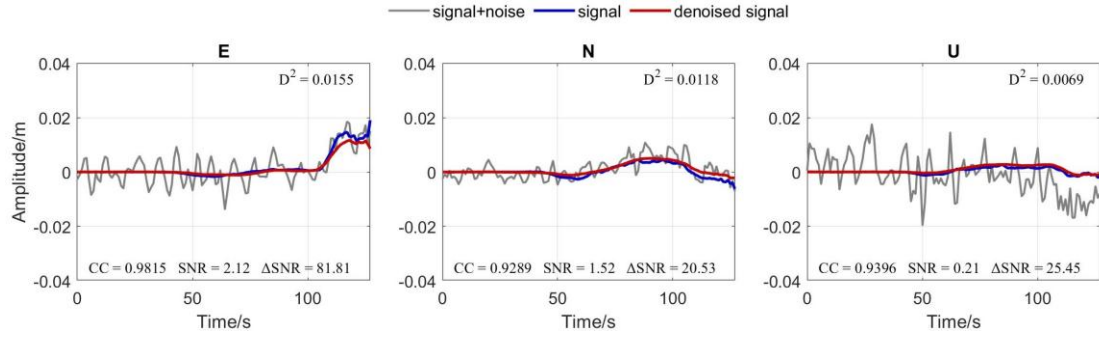


Fig.5 Denoising results on the test dataset (low SNR in all three directions,). Panels are the same as those in Fig. 4.

Figure 5 further evaluates the denoising performance under challenging conditions where the initial SNR in all three directions are relatively low, with values of 2.12 (E), 1.52 (N), and 0.21 (U), respectively. After processing with the proposed method, the values of CC for all three directions exceed 0.99, and the SNRs are improved by factors of 38.59, 13.51, and 121.19, respectively. Notably, even when the initial SNR in the U direction is as low as 0.21, the method effectively recovers key signal features such as the arrival time, amplitude, and frequency. This indicates its stable and balanced denoising performance of the proposed model under multi-directional low-SNR conditions.

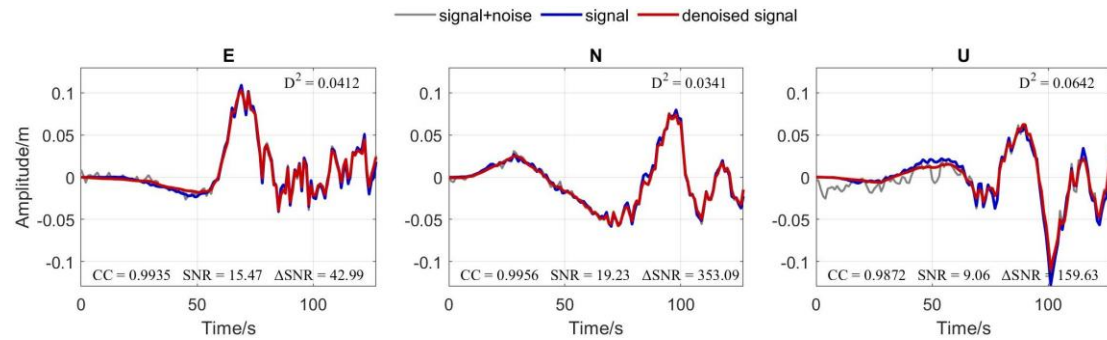


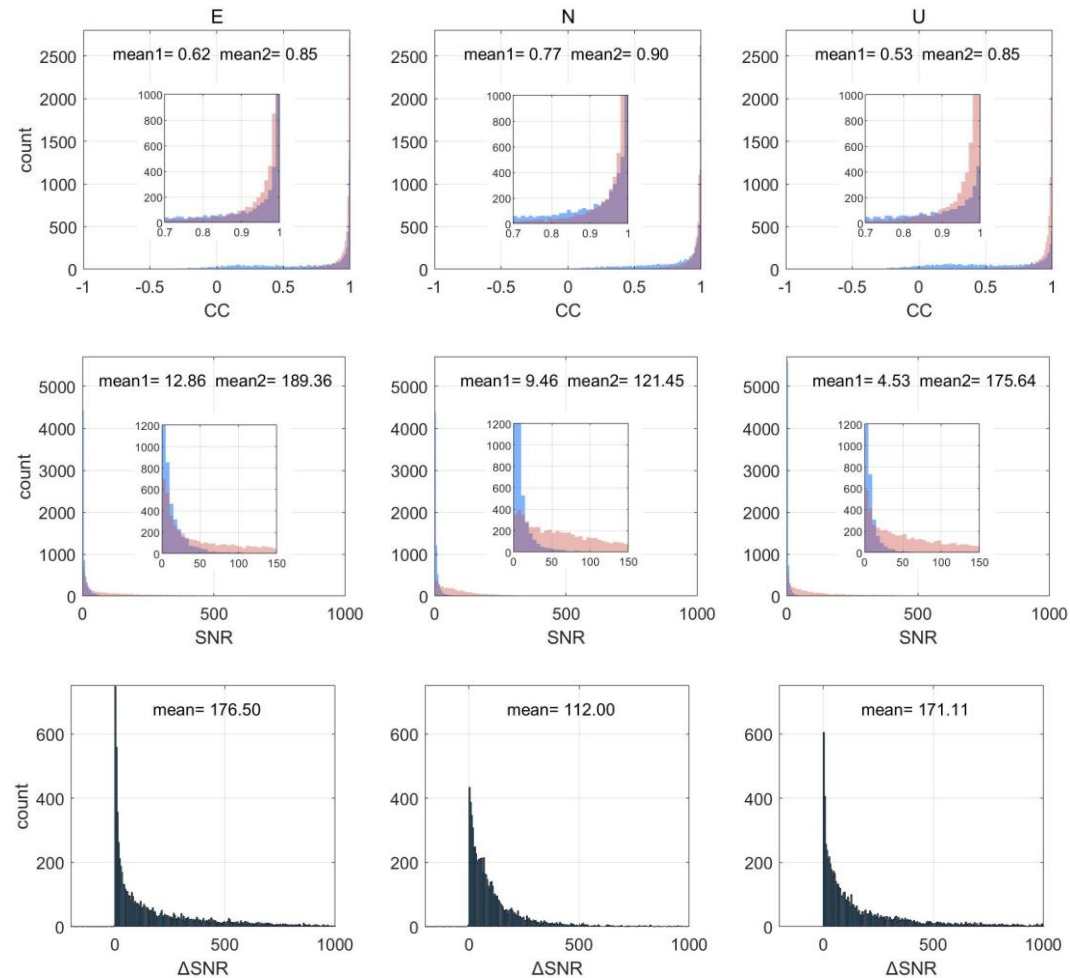
Fig.6 Denoising results on the test dataset (high SNR in all three directions,). Panels are the same as those in Fig. 4.

Figure 6 shows the denoising results under ideal conditions with large signal amplitudes and high initial SNRs. Although the noisy signals already possess relatively high SNRs, the proposed method further enhances the signal quality. After denoising, the CCs in the E, N, and U directions all reach 0.99, approaching perfect correlation. This result confirms the ability of the proposed method to preserve waveform fidelity

and achieve distortion-free enhancement under high-SNR conditions. Taken together with the previous test cases under diverse SNR conditions, the proposed method demonstrates applicability not only in common high-SNR environments but also exhibits excellent adaptability in challenging conditions such as low SNR and non-uniform SNR distribution. This provides a reliable and robust technical approach for processing high-rate GNSS seismic waveforms.

4.2 Quantitative Statistical Analysis

To systematically evaluate the overall performance of the proposed method on the test dataset (N=7098), a comprehensive quantitative analysis was conducted from three perspectives: signal correlation, SNR improvement, and geometric distance. The differences between the real signal, noisy signal, and denoised signal were assessed using the CC, SNR, and Euclidean distance (D^2) as evaluation metrics. The statistical results are shown in Fig.7.



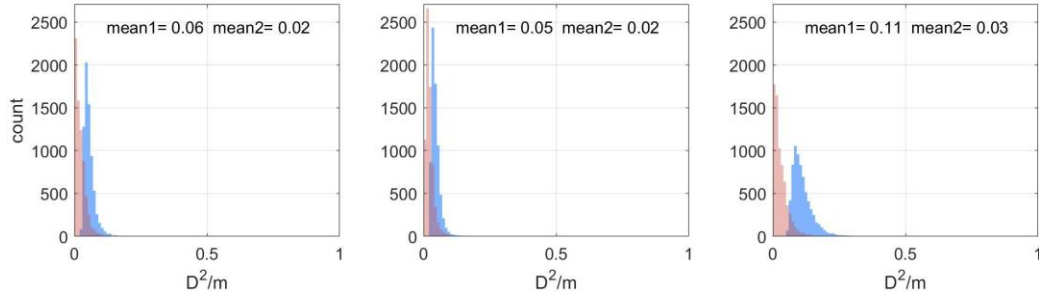


Fig.7 Quantitative statistical comparison of parameter metrics before and after denoising. The blue and red bars represent the results for noisy and denoised signals, respectively. In each subplot, mean1 and mean2 denotes the average value of the noisy signal and the denoised signal, respectively. The bar width for CC and $D^2 h$ is 0.01, and for SNR and ΔSNR the bar width is 5.

The first row of Fig. 7 illustrates the changes in CC before and after denoising. After applying the proposed method, the average CC values in the E, N, and U directions significantly increase from 0.62, 0.77, and 0.53 to 0.85, 0.90, and 0.85, respectively. This indicates that the denoised waveform is highly consistent with the real signal in both time and frequency domains. The most notable improvement is observed in the U direction further confirming the effectiveness of the method in recovering weak signals.

The SNR distribution in the second row of Fig. 7 show that, prior to denoising, most SNR values fall within the 0–30 range, whereas after denoising the number of SNR values in this range substantially decreases, reflecting the effective noise suppression. Quantitatively, the average SNR values in the E, N, and U directions improve from 12.86, 9.46, and 4.53 to 189.36, 121.45, and 175.64, corresponding to enhancements by factors of 14.72, 12.84, and 38.77, respectively. It is noteworthy that although the initial SNR is lowest in the U direction, it achieves the greatest relative gain. This result demonstrates the capability of the proposed method to leverage information from the higher-SNR horizontal directions to enhance vertical signal recovery, reflecting the synergistic effect of multi-directional information fusion.

The third row further presents the average SNR improvements (ΔSNR) of 176.50, 112.00, and 171.11 in the E, N, and U directions, respectively, reconfirming the overall denoising effectiveness from the perspective of SNR gain. The fourth row displays the changes in D^2 values before and after denoising. The average D^2 values in the E, N, and

U directions decrease from 0.06, 0.05, and 0.11 m to 0.02, 0.02, and 0.03 m, respectively, indicating that the denoised signals are closer to the real ones in both amplitude and waveform. The most pronounced reduction occurs in the U direction, further validating the superiority of the method in signal fidelity.

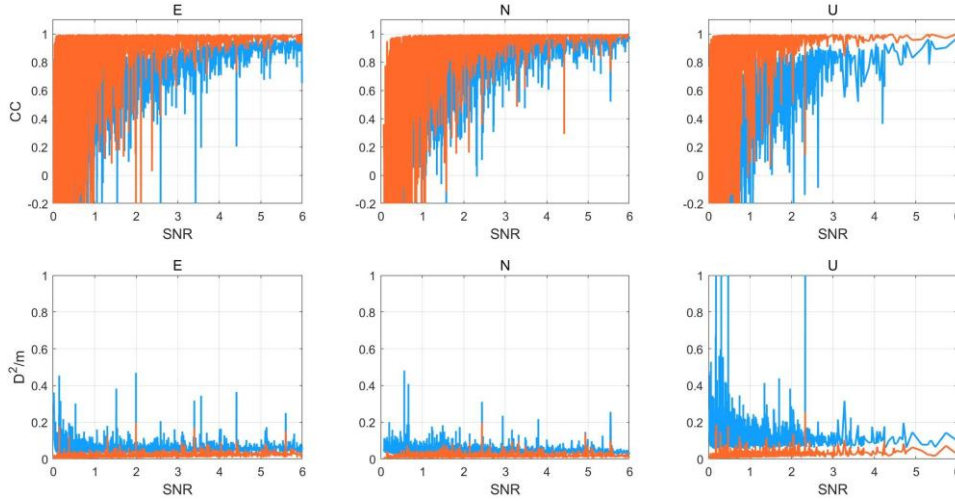


Fig.8 Relationships between CC/ D^2 and SNR. Blue and orange markers represent the noisy and denoised signals, respectively.

To further investigate the applicability and stability of the proposed method under low signal-to-noise ratio ($\text{SNR} \in [0, 6]$) conditions, Fig. 8 shows the variation of CC and D^2 with respect to SNR, systematically evaluating the boundary performance of the method from the perspectives of correlation and error distance.

As shown in the first row of Fig. 8, CC is positively correlated with SNR: higher SNR corresponds to stronger signal correlation. In the extremely low SNR region ($\text{SNR} < 1$), the difference in CC values before and after denoising is not significant, indicating that noise dominates under such conditions and the signal structure is difficult to extract. When SNR value lies in the range of 1–2, the denoised signal already exhibit higher CC values than the noisy signal, suggesting that the proposed method begins to show denoising effectiveness. When SNR values lie in the range of 2–4, the denoised signals achieve significantly higher CC values than the noisy signals, confirming ability of the proposed method to improve signal quality at low-to-moderate SNRs. As SNR increases further (> 4), the gain in CC gradually diminishes because the original CC approaches saturation and the noise contribution decreases, reflecting the stable performance of the proposed method on higher-quality signals. Moreover, the CC

values in the horizontal directions are generally higher than in the vertical direction, owing to larger signal amplitudes and lower noise levels in the horizontal components.

The second row of Fig. 8 indicates a clear negative correlation between D^2 and SNR: higher SNR leads to smaller Euclidean distances between noisy and real signals. Across all SNR levels, the D^2 of denoised signals is consistently lower than that of noisy signals, with the most pronounced reduction observed in the vertical direction. This further demonstrates the method can effectively reduce amplitude discrepancies between the denoised and true waveforms. In the horizontal directions, D^2 is already relatively low at low SNRs, and as SNR increases, the D^2 between the denoised signal and the real signal gradually converges and stabilizes. Under low SNR conditions, although the D^2 in the U direction is relatively large, mainly due to the influence of strong high-frequency noise and relatively weak signal amplitude in the vertical direction. Nevertheless, the D^2 after denoising is still lower than that of the noisy signal, indicating that the method still maintains a reasonable level of error control even in challenging conditions.

In summary, the proposed method exhibits effective denoising performance across the test dataset, maintaining robust noise suppression and signal enhancement particularly under low-SNR conditions. It not only improves signal correlation but also effectively reduces waveform amplitude errors, offering a reliable processing solution for low-quality GNSS data commonly encountered in practical seismic monitoring.

5 Application to the 2018 Anchorage earthquake

To systematically validate the noise reduction reliability of the proposed method for actual observational data, this study takes the 2018 Anchorage, Alaska Mw7.0 earthquake as an example. The earthquake occurred at 17:29:29 UTC on 30 November 2018, with an epicenter at (61.340°N, 149.937°W) and a focal depth of 40.9 km. Data from eight GNSS stations with a sampling rate of 1 Hz were selected, including two collocated GNSS (1 Hz) and strong-motion (SM) station pairs with sampling rate of 200 Hz and 50 Hz, the spatial distribution of which is shown in Fig. 9, and station details are provided in Table 1. The measured GNSS data were processed

using the PRIDE PPP-AR software (Geng J et al. 2019) to obtain coseismic displacement time series for each station.

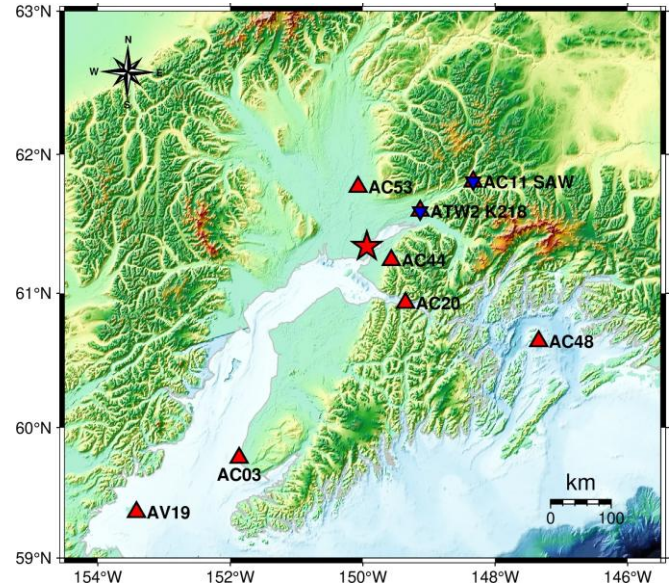


Fig.9 Epicenter and station distribution. The red star indicates the epicenter of the 2018 Anchorage, Alaska earthquake. Red triangles represent the GNSS stations used in this study, and blue inverted triangles denote strong-motion stations.

Table 1 Information on HR-GNSS and Co-located Strong-Motion (SM) Stations

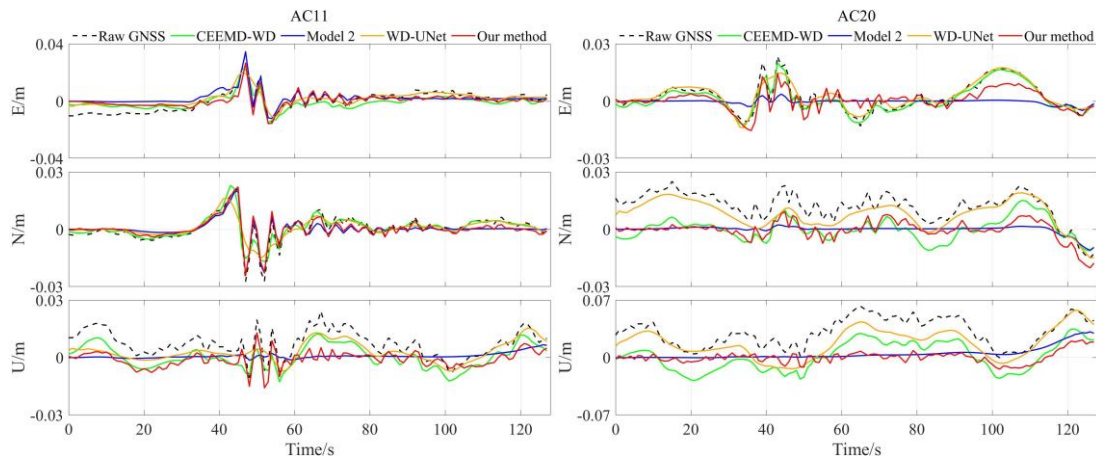
Station Type	Station Name	Latitude (°)	Longitude (°)	Epicentral Distance(km)
GNSS	AC03	59.771	-151.865	204.3
	AC11	61.807	-148.332	99.9
	AC20	60.929	-149.353	55.6
	AC44	61.242	-149.567	22.6
	AC48	60.646	-147.343	160.3
	AC53	61.769	-150.069	48.3
	ATW2	61.598	-149.132	51.7
	AV19	59.355	-153.414	292.8
SM	K218	61.593	-149.133	51.3
	ATW2	61.598	-149.132	51.7
SM	SAW	61.807	-148.332	99.9
	AC11	61.807	-148.332	99.9

5.1 Results analysis of high-rate GNSS coseismic displacement

Figures 10 and 11 present a comparative analysis of the coseismic displacements processed by four methods: CEEMD-WD, Model 2 proposed by Thomas A et al. (2023), WD-UNet, and the proposed CEEMD-UNet method, for GNSS stations located within and beyond 100 km from the epicenter, respectively. The original GNSS displacements contain considerable random noise and systematic errors, which obscure the seismic

signal. After denoising with the proposed method, the seismic signal becomes clearer, and its peak features as well as temporal stability show good agreement with the original displacement. In comparison, the CEEMD-WD method exhibits limited noise suppression for low-frequency components and notably underestimates signal peaks. The Model 2 approach tends to over-denoise at certain stations, particularly in the vertical component, causing amplitude distortion. For instance, the amplitudes in U direction at stations AC11 and AC44 are significantly compressed. Meanwhile, the WD-DL method excessively smooths the signals and likewise underestimates amplitudes, leading to substantial signal loss.

For stations farther from the epicenter (Fig. 11), where the original signal is weak, CEEMD-WD fails to extract meaningful seismic information, and Model 2 produces distorted waveforms. The proposed method, however, still extracts reliable seismic signals under these challenging conditions, demonstrating its strong adaptability to low-SNR data. This comparative analysis systematically validates the superiority of the proposed CEEMD-UNet method in handling varying noise levels and epicentral distances, highlighting its balanced performance in noise suppression and signal fidelity preservation.



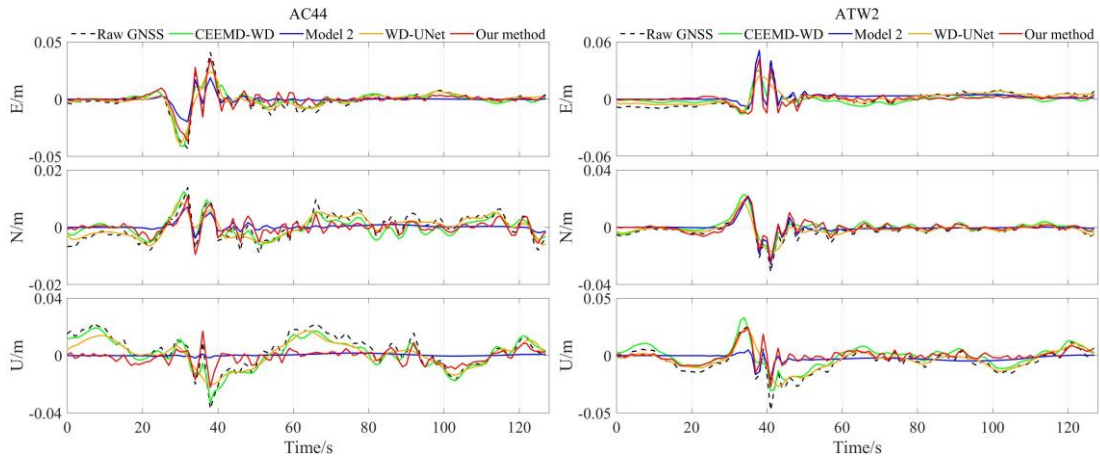


Fig.10 Comparison of waveforms before and after denoising for stations with epicentral distances less than 100 km. The stations include AC11, AC20, AC44, and ATW2. The black dashed line represents GNSS displacements; The solid green, blue, orange, and red lines represent displacements denoised by CEEMD-WD, Model 2 proposed by Thomas A et al. (2023), WD-UNet, and the proposed CEEMD-UNet methods, respectively.

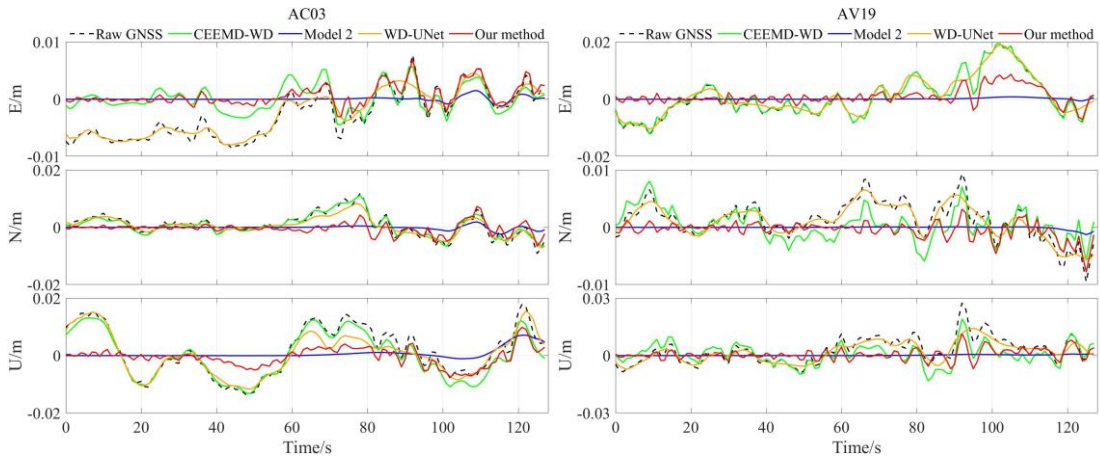


Fig.11 Comparison of waveforms before and after denoising for stations with epicentral distance larger than 100 km. The stations include AC03 and AV19. Panels are the same as those in Fig. 10.

To quantitatively evaluate the reliability of the performance of the proposed denoising method, we calculated the Root Mean Square (RMS) error and SNR in the E, N, and U directions for all stations before and after denoising (Fig.12).

Overall, all four denoising methods reduce RMSE and improve the SNR, with the proposed method yielding the most significant improvement. Before denoising, the average RMSE values of the coordinate residuals across all stations in the E, N, and U directions are 0.77, 0.79, and 1.45 cm, respectively. After applying the proposed method, these values decreased to 0.45, 0.40, and 0.46 cm, representing reductions of 41.39%,

48.79%, and 67.90%. In terms of SNR, the original average SNR values in the three directions are 3.84, 5.60, and 4.35, which rise to 23.24, 21.79, and 8.52 after the proposed CEEMD-UNet denoising. Although the RMSE values of Model 2 and WD-UNet are slightly lower than those of the proposed method for certain directions at individual stations, waveform comparisons indicate that this difference results from excessive denoising by Model 2 and WD-UNet, which leads to substantial amplitude loss. In summary, the proposed method effectively suppresses noise while better preserving the amplitude and temporal features of seismic signals, achieving a more favorable balance between improving data quality and retaining useful information.

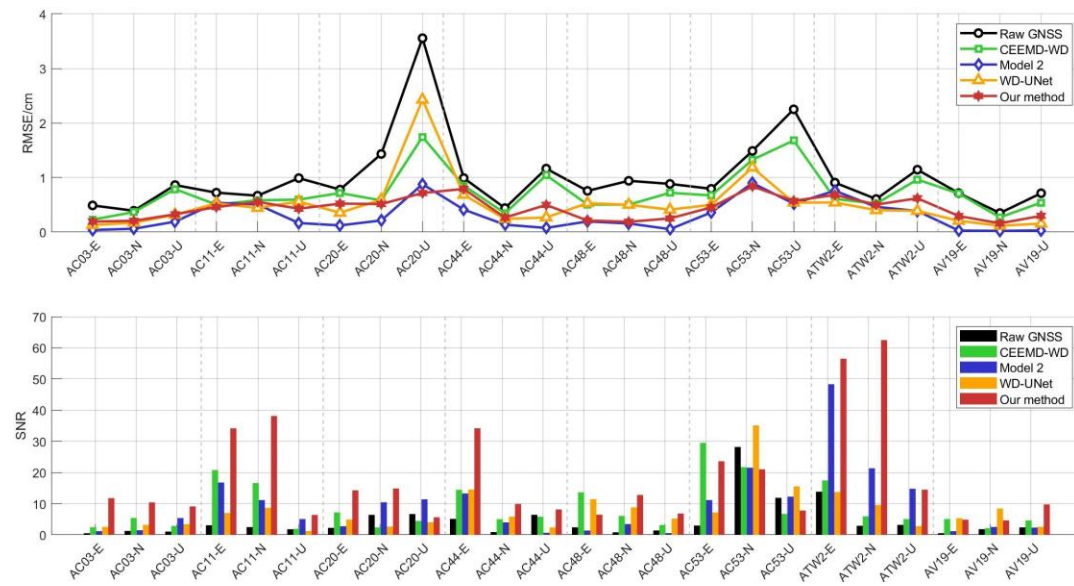


Fig.12 Comparison of RMSE (top) and SNR (bottom) in three directions before and after denoising for all stations.

5.2 Denoising results analysis of co-located coseismic displacement

Herein, the co-located stations, K218/ATW2 (strong-motion/GNSS) and SAW/AC11 are selected to further validate the denoising performance. The proposed method is applied to process the seismic coseismic displacement records from the GNSS stations, and its performance is compared against three other denoising methods: CEEMD-WD, Model 2, and WD-UNet. The waveform comparison results are presented in Figures 13. To quantitatively assess the denoising effectiveness, the RMSE and SNR of the high-rate GNSS data were calculated for both the raw and denoised versions, with the statistical results summarized in Table 2.

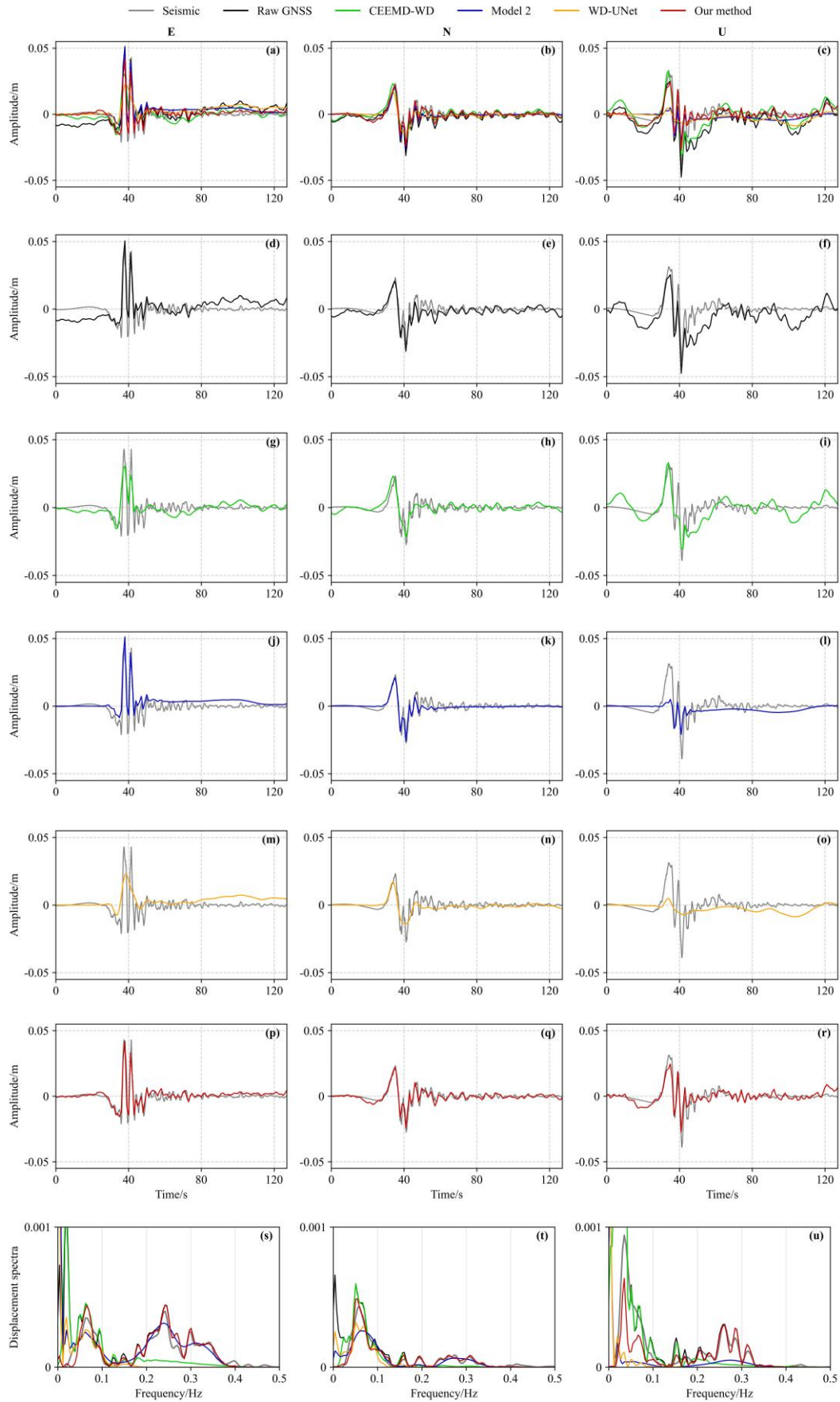


Fig.13 Denoise comparison at GNSS Station ATW2. Using the strong-motion records as the

reference: (a)-(c) compare the full displacement waveforms; (d)-(r) compare the denoised waveforms from each method with respect to the strong-motion waveforms; (s)-(u) show the power spectral density curves.

Figure 13(a)-(r) presents the denoising results for the coseismic displacements at the co-located station K218/ATW2. In terms of waveform consistency with the strong-motion records, the waveforms processed by the proposed method exhibit the closest agreement, showing overall higher similarity. In contrast, the CEEMD-WD method provides limited denoising effectiveness, remaining closer to the original high-rate GNSS waveforms. The Model 2 method noticeably underestimates signal amplitudes in some cases, especially in the U component. The WD-UNet method excessively smooths certain important seismic features and similarly suffers from amplitude underestimation. Although the first three methods suppress noise in the original GNSS data to some extent, thereby improving signal reliability, the proposed method achieves more accurate amplitude recovery and better preserves useful signal components while removing noise.

Figure 13(s)-(u) shows the power spectral density (PSD) curves of the signals. In the low-frequency band (0–0.1 Hz), the PSD of the proposed method is the closest to that of the strong-motion data, indicating its superior performance in low-frequency noise suppression and its ability to retain the original spectral characteristics. Conversely, the CEEMD-WD and WD-UNet methods show noticeable deviations in the low-frequency band, reflecting their limitations in low-frequency noise denoising. The performance of the Model 2 method falls between the CEEMD-WD and WD-UNet methods but overall matches the strong-motion spectra less closely than the proposed method. In the mid-to-high frequency range (0.1–0.5 Hz), the curves of all methods gradually converge, though differences remain observable.

The energy distribution of the proposed method agrees best with the strong-motion record, whereas the other methods may suffer from excessive smoothing or residual noise in this band. Through comparison of the PSD curves, the proposed method demonstrates the best performance in preserving the original spectral features, especially in the low-frequency band, where its denoising effect is notably superior to

the other approaches.

Table 2 Statistics of RMSE and SNR before and after denoising at station ATW2

	RMSE/mm			SNR		
	E	N	U	E	N	U
Raw GNSS	6.59	3.38	8.49	0.10	4.84	0.26
CEEMD-WD	5.22	3.08	7.09	2.02	4.18	-0.06
Model 2	5.05	2.20	6.04	4.23	7.27	1.88
WD-UNet	6.71	3.00	6.96	1.00	4.68	0.69
Our method	3.61	2.04	3.89	5.44	7.83	5.09

Table 2 lists the RMSE and SNR statistical results at station ATW2, which are largely consistent with the aforementioned waveform analysis. In terms of RMSE reduction relative to the original GNSS data, the CEEMD-WD method reduces RMSE in the E, N, and U directions by 20.78%, 8.91%, and 16.51%, respectively. The Model 2 method achieves reductions of 23.28%, 34.97%, and 28.83% in the same directions. The WD-UNet method increases RMSE slightly in the E direction, while reducing it by 11.14% in N and 18.06% in U. The proposed CEEMD-UNet method yields the largest improvements, with RMSE reductions of 45.22%, 39.79%, and 54.16% in the E, N, and U directions, respectively. Regarding SNR improvement, both Model 2 and the proposed method show notable gains compared to the original high-rate GNSS signals. The SNR values increase by 4.13, 2.43, and 1.62 for model2, and by 5.34, 2.99, and 4.83 for the proposed method in the E, N, and U directions, respectively. In contrast, the SNR results after CEEMD-WD and WD-UNet denoising remain close to those of the raw data, reflecting their limited ability to suppress low-frequency noise.

Overall, both Model 2 and the proposed method substantially reduce noise and improve signal quality. While the horizontal performance of the proposed method is comparable to that of Model 2, it outperforms Model 2 in the vertical direction, where GNSS signals generally exhibit lower initial SNR. These results further demonstrate the superior noise suppression and signal fidelity of the proposed method under low-SNR and structurally complex conditions, enabling more accurate recovery of the true dynamic characteristics of seismic waveforms.

5 Conclusions

High-rate GNSS coseismic displacement data often suffer from low signal-to-noise ratio (SNR) in the case of moderate-magnitude earthquakes or at distant stations. Conventional denoising methods are limited by linear assumptions or mode-mixing issues, or tend to over-denoise and distort amplitudes, failing to balance noise suppression with signal fidelity. To address these limitations, a feature-preserving deep-denoising method based on Complete Ensemble Empirical Mode Decomposition and U-Net Convolutional Neural Network (CEEMD-UNet) is proposed. The method first applies CEEMD to adaptively decompose non-stationary signals, effectively mitigating mode-mixing and separating noise from meaningful components, thereby providing structured inputs for subsequent processing. Leveraging the strong feature extraction and nonlinear mapping capabilities of the UNet network, the method achieves accurate denoising of each intrinsic mode function. Additionally, a multi-direction information fusion mechanism is introduced to enhance the recovery of weak signals in the vertical component. The framework adapts to different SNR levels, addressing performance degradation under low-SNR conditions and over-smoothing under high-SNR conditions. Through systematic denoising experiments on both synthetic and real high-rate GNSS displacement data, the performance of the proposed method is comprehensively evaluated, leading to the following conclusions:

- 1) In tests on the synthetic dataset, the proposed method yields average cross-correlation coefficients above 0.85 in all three components, and improves the average SNR by factors of 14.72, 12.84, and 38.77 in the E, N, and U directions, respectively. Evaluations across three typical SNR scenarios demonstrate that the method significantly enhances SNR under low-SNR conditions while further refining waveform quality under high-SNR conditions, showing robust adaptability.
- 2) Validation using real data from the 2018 Mw 7.0 Anchorage, Alaska earthquake shows that the average RMSE across eight high-rate GNSS stations is reduced by 41.39% to 67.90% in the three components, while the average SNR is

increased by factors of 5.05, 2.89, and 0.96, respectively. Compared with CEEMD-WD, Model 2, and WD-UNet methods, the proposed method effectively preserves seismic waveform features in high-rate GNSS displacement time series, and reliably extracts useful seismic information even at distant stations with weak signals.

- 3) Although the model was trained on synthetic data from the Chilean subduction zone, it exhibits clear advantages in waveform consistency, amplitude preservation, and cross-scenario adaptability when applied to the 2018 Anchorage earthquake data, demonstrating good generalization capability across different regions.

The proposed feature-preserving deep-denoising method (CEEMD-UNet) effectively integrates conventional signal decomposition with deep learning, overcoming the amplitude distortion often encountered by deep-learning models under low-SNR conditions and achieving more accurate noise identification and signal reconstruction. This method not only provides a reliable technical means for improving the quality of high-rate GNSS data, but also holds considerable application value in fields such as earthquake early warning and source parameter inversion.

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