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A Physics-Informed Neural Network Framework for Seismic Signal Denoising Based on Time–Frequency Adaptive Decomposition

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Abstract

Seismic signal denoising stands as a vital process that enables precise seismic data analysis because noise interference blocks the detection of weak but valuable seismic signals. The current traditional denoising methods together with deep learning-based data-driven approaches encounter difficulties when they need to remove noise from seismic signals while keeping their fundamental structural elements, especially under conditions of low signal-to-noise ratios. In this study, we propose a novel denoising framework that integrates a physics-guided neural network with adaptive time–frequency decomposition, referred to as TF-PhysNet. The system breaks down broadband seismic data into separate frequency bands. Scientists can use these to study specific noise patterns that appear at various frequency points. The system uses a shared convolutional neural network-long short-term memory architecture to remove noise from each sub-band, which helps it learn both short-term waveform patterns and extended temporal relationships. The system uses physics-guided restrictions to eliminate false signal variations, which appear during the signal recovery process. The experimental findings from synthetic and real seismic data sets show that TF-PhysNet delivers better results than standard denoising techniques and deep learning-based methods for signal-to-noise ratio improvement and correlation coefficient enhancement.

Keywords: seismic data denoising; physics-guided neural network; machine learning; adaptive time–frequency decomposition



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1. Introduction

Seismic data are widely used in engineering geophysics, where data quality is critical for ensuring the reliability and accuracy of practical applications. In realistic acquisition environments, recorded seismic data are inevitably affected by environmental noise, human activities, and equipment limitations, which significantly reduce the signal-to-noise ratio (SNR) and may obscure weak seismic signals carrying valuable geological information. Consequently, seismic data denoising constitutes a fundamental prerequisite for subsequent seismic response analysis of structures.

Conventional earthquake signal denoising methods are typically developed based on predefined assumptions regarding the underlying signal and noise models. In general, seismic denoising techniques can be broadly categorized into transform- or decomposition-based methods, as well as alternative approaches such as low-rank modeling. Adaptive singular value decomposition has been extensively investigated in both the time and frequency domains to enhance noise attenuation performance [1,2]. In addition, low-rank tensor modeling has been employed to exploit structural redundancies in seismic data for the suppression of stochastic noise [3,4]. Time–frequency analysis constitutes another major class of denoising algorithms [5–8], in which noisy seismic signals are transformed into the time–frequency domain to increase signal sparsity and facilitate effective separation from noise [9–11]. However, these approaches may become less effective when seismic noise exhibits strong non-stationarity or when the signals possess complex spectral characteristics.

With recent advances in deep learning, data-driven approaches to seismic denoising have attracted increasing research attention. Early studies demonstrated that deep learning techniques can effectively suppress seismic noise and automatically extract useful signal components without the need for manually designed filters [12–14]. By exploiting their ability to learn informative features in both the time and frequency domains, these methods provide a powerful alternative to conventional seismic denoising schemes. Deep learning-based approaches often incorporate time–frequency representations to automatically learn discriminative signal features from seismic data, thereby achieving enhanced noise attenuation performance [15–17]. In parallel, signal processing methods based on optimal empirical wavelet transforms combined with adaptive thresholding have been applied to suppress random seismic noise while preserving essential waveform characteristics [18,19]. More recent studies have proposed a wide range of multi-architecture deep learning models for seismic denoising, aiming to improve robustness and stability under complex and nonstationary noise conditions, including networks with advanced attention mechanisms, hybrid domain representations, and segmented modeling strategies [20–24].

Residual learning strategies have further enhanced the stability and performance of deep learning-based denoising models. Originally developed for computer vision applications, residual network concepts inspired denoising architectures such as DnCNN [25], which were subsequently adapted to seismic signal processing through deep residual networks and DnCNN-based models [26–29]. In parallel, hybrid network architectures that integrate convolutional and recurrent neural networks have received increasing attention. In particular, CNN-LSTM fusion models have been investigated to capture both local waveform features and long-range temporal dependencies in seismic data [30]. However, many existing deep learning-based denoising approaches operate directly on broadband seismic signals and rely primarily on data-driven optimization objectives, often overlooking the intrinsic frequency-dependent characteristics of seismic noise. Moreover, explicit physical consistency constraints are rarely incorporated into these models. As a result, such limitations may lead to waveform distortion and reduced robustness, especially under low SNR conditions.

To address these limitations in seismic denoising, we develop a time–frequency adaptive decomposition and physics-guided neural network framework. Within this framework, broadband seismic signals are adaptively partitioned into multiple frequency sub-bands, enabling explicit modeling of frequency-dependent noise characteristics. An optimization strategy based on the Mountain Gazelle Optimizer (MGO) is employed to determine the optimal frequency boundaries for sub-band decomposition [31]. Furthermore, to ensure that waveform reconstruction remains physically meaningful during network training, a physics-guided learning strategy is incorporated into the parameter update process,

drawing on previous studies of physics-informed deep learning and neural-network-based denoising models [32–34]. Experimental results obtained from both synthetic and real seismic datasets demonstrate that the proposed TF-PhysNet achieves superior denoising performance compared with conventional methods and existing deep learning models.

2. Methodology

Seismic signal denoising aims to suppress various types of noise present in observed seismic records while recovering the underlying clean seismic signal as accurately as possible. In practical data acquisition, a recorded seismic signal can generally be modeled as a superposition of the true seismic signal and noise, which can be expressed as

$$y(t) = s(t) + n(t) \quad (1)$$

where $y(t)$ denotes the observed noisy seismic signal, $s(t)$ represents the clean seismic signal, and $n(t)$ corresponds to noise arising from environmental disturbances, anthropogenic activities, and instrumental effects. The objective of seismic denoising is to estimate a denoised signal $\hat{s}(t) = s(t)$.

2.1. Overall Framework

A time–frequency adaptive decomposition combined with a physics-guided neural network is proposed for seismic signal denoising. Unlike purely data-driven methods, this framework explicitly considers the frequency-dependent nature of seismic noise, which is often overlooked when the physical structure is not taken into account. The complete denoising workflow is organized into seven successive stages, as outlined in Figure 1.

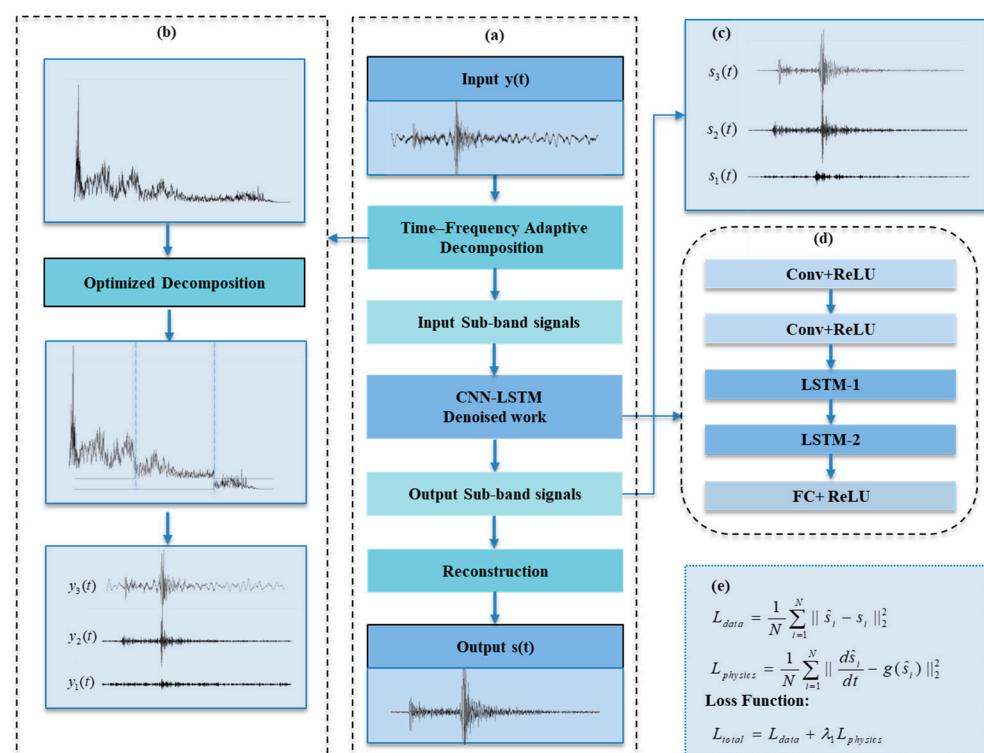


Figure 1. Overview of the time–frequency adaptive decomposition and physics-guided denoising framework. (a) Main denoising workflow; (b) time–frequency adaptive decomposition; (c) denoised output sub-band signals; (d) CNN-LSTM network architecture; and (e) physics-guided loss function.

Before network inference, the noisy seismic trace is first analyzed by a time–frequency adaptive decomposition module. This module inspects the spectral distribution of the input

signal and, through an optimization-based strategy, adaptively determines the appropriate decomposition boundaries. Following this step, the broadband noise-contaminated seismic signal is partitioned into three representative sub-bands corresponding to low-, mid-, and high-frequency ranges defined by the adaptive boundaries. While each sub-band retains the temporal characteristics of the original signal, it simultaneously highlights distinct spectral features, allowing frequency-specific noise patterns to be addressed more effectively. The resulting noisy sub-band signals are then fed into a shared CNN–LSTM denoising network. Within this network, the convolutional layers are primarily responsible for extracting sparse temporal features and attenuating components dominated by noise in each sub-band, whereas the LSTM layers focus on modeling the long-term temporal dependencies associated with seismic wave propagation. From this standpoint, sharing network parameters across all sub-bands not only reduces the overall model complexity but also encourages consistent feature representation across different spectral regions.

The network produces denoised outputs for each frequency sub-band, which are subsequently merged through a reconstruction module to form the final denoised seismic signal. During training, a physics-guided learning strategy is incorporated by introducing physics-consistency constraints alongside the data-consistency term. These constraints, derived from the fundamental relationships among acceleration, velocity, and displacement, serve to suppress non-physical oscillations and guide the network toward physically plausible waveform reconstruction.

2.2. Time–Frequency Adaptive Decomposition

Seismic waves are characterized by intricate spectral behavior arising from heterogeneous subsurface media and the coexistence of multiple noise sources. In practical seismic records, informative signal components are usually concentrated within certain frequency intervals, while noise tends to spread across a much wider spectral range. Because of this imbalance, suppressing noise in broadband seismic data is far from trivial, especially when frequency-domain separation is not explicitly considered. From this perspective, ignoring spectral structure often leads to either residual noise or the loss of useful signal content.

Within the Time–frequency adaptive decomposition (TFAD) module, the input noisy seismic signal is first transformed from the time domain into the frequency domain to facilitate spectral analysis. A noisy signal in the time domain $y(t)$ is converted into the frequency domain using the discrete Fourier transform (DFT), which is computationally implemented via the fast Fourier transform (FFT) algorithm:

$$Y(f) = \mathcal{F}\{y(t)\} \quad (2)$$

where $\mathcal{F}\{\cdot\}$ denotes the discrete Fourier transform and f represents the frequency index. This transformation yields a global spectral representation of the seismic signal and enables analysis of its frequency-dependent energy distribution.

On the basis of the obtained spectral representation, the TFAD module conducts adaptive frequency partitioning using an optimal scheme guided by an optimization strategy. Specifically, the Mountain Gazelle Optimizer (MGO) algorithm is adopted to identify the optimal frequency boundaries according to the energy distribution of the input spectrum [23].

The adaptive frequency band partition is formulated as a parameter optimization problem, where the boundaries of three frequency sub-bands are treated as decision variables. For each candidate solution, the frequency spectrum is divided into three sub-bands according to the selected boundaries, and a fitness function is calculated to evaluate the quality of the partition. The MGO is employed to iteratively update the candidate boundaries and search for the optimal frequency band partition. It helps mitigate the problems of fixed

frequency partitions designed through manual methods. It makes feasible the separation of spectral components having varied statistical and structural patterns. The real seismic signals are 30 s in duration with 3000 samples, and the synthetic signals are 20 s in duration with 2000 samples; both are sampled at 100 Hz, yielding a Nyquist frequency of 50 Hz that defines the upper bound of the frequency partition.

The optimized frequency boundaries are defined as

$$0 = f_0 < f_1 < f_2 < f_3 = \frac{f_s}{2} \quad (3)$$

where f_s is the sampling frequency. Although the frequency boundaries are determined adaptively for each signal, the optimization is strictly constrained within the fixed range $\left[0, \frac{f_s}{2}\right]$. In practice, the optimized boundaries vary smoothly according to the spectral energy distribution of the signal and preserve the ordered structure. No abrupt boundary shifts were observed under different noise conditions, indicating that the adaptive partition remains structurally stable. Based on these limits, a three sub-band decomposition is applied to the frequency domain. Each sub-band component is obtained by applying a frequency-selection mask:

$$Y_k(f) = Y(f) \cdot M_k(f), k = 1, 2, 3 \quad (4)$$

where $M_k(f)$ is the mask for the k -th frequency band. After frequency partitioning, each sub-band component is transformed back into the time domain using the inverse discrete Fourier transform (IDFT), which is implemented computationally via the inverse fast Fourier transform (IFFT):

$$y_k(t) = \mathcal{F}^{-1}\{Y_k(f)\} \quad (5)$$

The sub-band signals retain waveform timing information as well as meaningful frequency-specific spectral details. These are then used as homogeneous inputs for the CNN-LSTM-based denoising network.

2.3. Network Structure

To suppress seismic noise, a CNN-LSTM-based neural network is employed as the core denoising component, operating in a sub-band-wise manner. For a noisy seismic record, the time–frequency adaptive decomposition (TFAD) module is first applied to obtain frequency sub-bands, after which the CNN-LSTM network is independently applied to each frequency component using shared parameters. This parameter-sharing strategy effectively reduces the overall model complexity while encouraging coherent feature learning across multiple frequency sub-bands. As a result, the network is better equipped to generalize when processing seismic signals with heterogeneous spectral characteristics. In practice, the input to the CNN–LSTM framework is organized as a three-dimensional tensor of size $B \times N \times 3$, where B denotes the batch size, N represents the number of temporal samples, and the third dimension corresponds to the three decomposed frequency sub-band components.

Within this architecture, the convolutional layers primarily focus on extracting local time-domain features while suppressing noise-dominated components in the seismic data [35]. By employing hierarchical convolutional operations in conjunction with nonlinear activation functions, the network progressively learns short-term temporal patterns that are intrinsic to seismic waveforms. The features obtained from the convolutional stage are then passed to the LSTM layers, which are responsible for modeling long-term temporal dependencies and maintaining phase continuity in the time domain [36]. Owing to their internal memory and gating mechanisms, LSTM units can effectively capture the dynamic evolution of seismic signals. From this perspective, they play a critical role in reinforcing

phase consistency and temporal coherence in the denoised output, particularly for signals with extended duration or complex temporal structure.

The CNN-LSTM architecture integrates convolutional and recurrent components to exploit their complementary strengths in seismic denoising [37]. While the convolutional layers emphasize localized feature extraction and the attenuation of short-scale noise, the LSTM layers focus on long-range temporal correlations and waveform continuity. This hybrid configuration helps mitigate the over-smoothing often observed in purely convolutional models and, at the same time, reduces the vulnerability of recurrent networks to high-frequency noise. Consequently, the proposed design achieves a more balanced denoising behavior, preserving fine-scale waveform details alongside the global temporal structure of seismic signals.

The denoising operation for the k -th frequency sub-band is defined as

$$\hat{y}_k(t) = \mathcal{F}_\theta(y_k(t)), k = 1, 2, 3 \quad (6)$$

where $y_k(t)$ denotes the input noisy signal in the k -th sub-band; $\hat{y}_k(t)$ represents the corresponding denoised output. The operator $\mathcal{F}_\theta(\cdot)$ represents the nonlinear transformation performed by the CNN-LSTM network with learnable parameters θ . The behavior of the temporal model of the recurrent module is given by the equation of the hidden state:

$$h_t = \mathcal{G}(h_{t-1}, x_t) \quad (7)$$

where x_t symbolically represents a feature vector extracted from the output of the convolutional layers corresponding to the time step t , and h_t denotes the latent variable representing the characteristics of the time-dependent behavior of seismic waveforms. By removing all the components of the sub-bands, the clean full-band signal of the seismological data is derived from the linear combination of the clean sub-bands as given below:

$$\hat{s}(t) = \sum_{k=1}^K \hat{y}_k(t) \quad (8)$$

where K denotes the total number of frequency sub-bands. This reconstruction procedure maintains synchrony in the time domain across sub-bands and accumulates information across disparate frequency bands.

2.4. Physics-Guided Loss Function

Although frequency-aware processing facilitates seismic denoising, purely pointwise optimization based on reconstruction accuracy may lead to over-smoothing or physically implausible waveform distortions, particularly for low-amplitude seismic events. In seismic signal denoising, preserving physically meaningful waveform evolution and temporal consistency is as critical as minimizing noise energy. To address this issue, a physics-guided multi-term loss function is introduced to guide network training toward physically plausible solutions.

The overall training objective is constructed as a weighted combination of data fidelity and physics-guided constraints:

$$L_{total} = L_{data} + \lambda_1 L_{physics} \quad (9)$$

where L_{data} measures the reconstruction accuracy of the denoised signal and $L_{physics}$ represents the physics-guided constraint term. The weighting coefficient λ_1 controls the trade-off between noise suppression and physical consistency. Its value is selected empirically based on validation performance.

The data fidelity term is defined using the mean squared error (MSE) between the denoised signal $\hat{s}(t)$ and the reference clean signal $s(t)$:

$$L_{data} = \frac{1}{N} \sum_{i=1}^N (\hat{s}_i - s_i)^2 \quad (10)$$

The loss function imposes a penalty for pointwise reconstruction error and tries to leverage the network output to be close to the reference seismic signal in an average sense. There is high temporal consistency and physically well-behaved dynamic patterns in seismic waveforms. Optimization that is data fidelity-seeking alone can pose unreasonable temporal variations, particularly for high levels of noise. A physics-guided constraint is therefore incorporated to regulate the temporal behavior of the denoised signal. This constraint penalizes inconsistencies in the temporal derivatives and is formulated as

$$L_{physics} = \frac{1}{N} \sum_{i=1}^N \left(\frac{d\hat{s}_i}{dt} - g(s_i) \right)^2 \quad (11)$$

where $\frac{d\hat{s}_i}{dt}$ denotes the temporal derivative of the denoised signal, and $g(\cdot)$ represents a physically motivated dynamic consistency operator derived from the fundamental kinematic relationships among displacement, velocity, and acceleration in elastic wave propagation. Although the full elastodynamic wave equation is not explicitly solved, this operator enforces a local approximation of the governing dynamic behavior, guiding the network toward physically plausible temporal evolution. The loss is computed pointwise over scalar temporal samples, which eliminates ambiguity between absolute value and vector norm representations.

3. Dataset and Data Preprocessing

The effectiveness of deep learning-based seismic denoising methods is strongly dependent on the quality of the training datasets. To address the challenges posed by complex seismic signals and the limited availability of labeled clean data, Real observed seismic waveforms and synthetically generated waveforms are used to independently evaluate and cross-validate the robustness of the proposed network. Signal processing procedures are applied to ensure the physical consistency and integrity of the training data used for the neural network model.

Real seismic waveforms are sourced from the Stanford Earthquake Dataset, a large collection of labeled seismic recordings derived from global seismic networks [38]. There are 500 earthquake events in total. Each event consists of a vertical-component waveform recorded at one station with a 30 s length and a sampling rate of 100 Hz. Event magnitudes span a wide range between about Mw 4.0 and 6.5, covering a broad range of seismic characteristics. Synthetic seismic data generated under controlled noise conditions complement the real dataset. The synthetic dataset first provides clean signals, which then get corrupted by adding Gaussian white noise to produce noisy observations. Due to its common seismic noise characteristics, Gaussian noise is adopted in this work. The signals are resampled to 100 Hz and segmented into 20 s windows; for each original signal, several SNR levels were generated by adjusting the noise amplitude.

All seismic recordings are run through the same preprocessing pipeline before training. We utilize a sliding-window approach to segment the continuous waveforms into fixed-size windows, allowing overlap to enhance dataset diversity and robustness. Normalization is

independently performed for each segment of the waveform segment to decrease amplitude variability. The normalization procedure is defined as

$$\tilde{v}_i = \frac{v_i}{\max|v|} \quad (12)$$

where v_i denotes the original waveform amplitude and $\tilde{v}_i$ represents the normalized signal. Waveform morphology is preserved, and numerical stability is improved during training.

4. Experiments on Synthetic Seismic Dataset

4.1. Evaluation Metrics

The denoising performance of TF-PhysNet is quantitatively evaluated using the SNR, correlation coefficient (r), mean squared error (MSE), and root mean squared error (RMSE). These metrics are widely adopted in seismic signal processing to assess noise suppression effectiveness and signal reconstruction quality.

$$\text{SNR} = 10 \log_{10} \left(\frac{\sum_{i=1}^N s_i^2}{\sum_{i=1}^N (s_i - \hat{s}_i)^2} \right) \quad (13)$$

$$r(s, \hat{s}) = \frac{\text{Cov}(s, \hat{s})}{\sqrt{\text{Var}(s) \text{Var}(\hat{s})}} \quad (14)$$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (s_i - \hat{s}_i)^2 \quad (15)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (s_i - \hat{s}_i)^2} \quad (16)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (17)$$

where s is the reference clean seismic signal, $\hat{s}$ is the denoised signal, and N is the length of the signal. In Equation (13), the denominator calculates the noise energy before denoising, while the denominator in Equation (14) calculates the covariance between the clean and denoised signals. $\text{Cov}(s, \hat{s})$ calculates the covariance between the clean and denoised signals, and $\text{Var}(s)$ and $\text{Var}(\hat{s})$ denote their variances. r reflects waveform similarity between the denoised signal and the reference signal.

4.2. Results on Synthetic Dataset

Experiments are performed on both synthetic and real-world seismic signals to comprehensively assess the denoising performance of TF-PhysNet. The proposed method is compared with wavelet denoising approach, the empirical mode decomposition (EMD) approach, and the DnCNN approach.

As shown in Figure 2b, the seismic signal is severely contaminated by noise, exhibiting large-amplitude fluctuations and irregular high-frequency oscillations. Under such severely noisy conditions, reliable identification of key waveform characteristics, including phase onsets and amplitude maxima, becomes highly challenging. Wavelet-based and EMD denoising methods are able to attenuate the influence of contaminating noise, particularly high-frequency components, but residual noise and oscillations remain, which continue to disrupt waveform continuity. The DnCNN-based approach is capable of achieving relatively strong noise suppression; nonetheless, it tends to introduce excessive smoothing in transitional regions, which in turn leads to the attenuation of fine-scale waveform details.

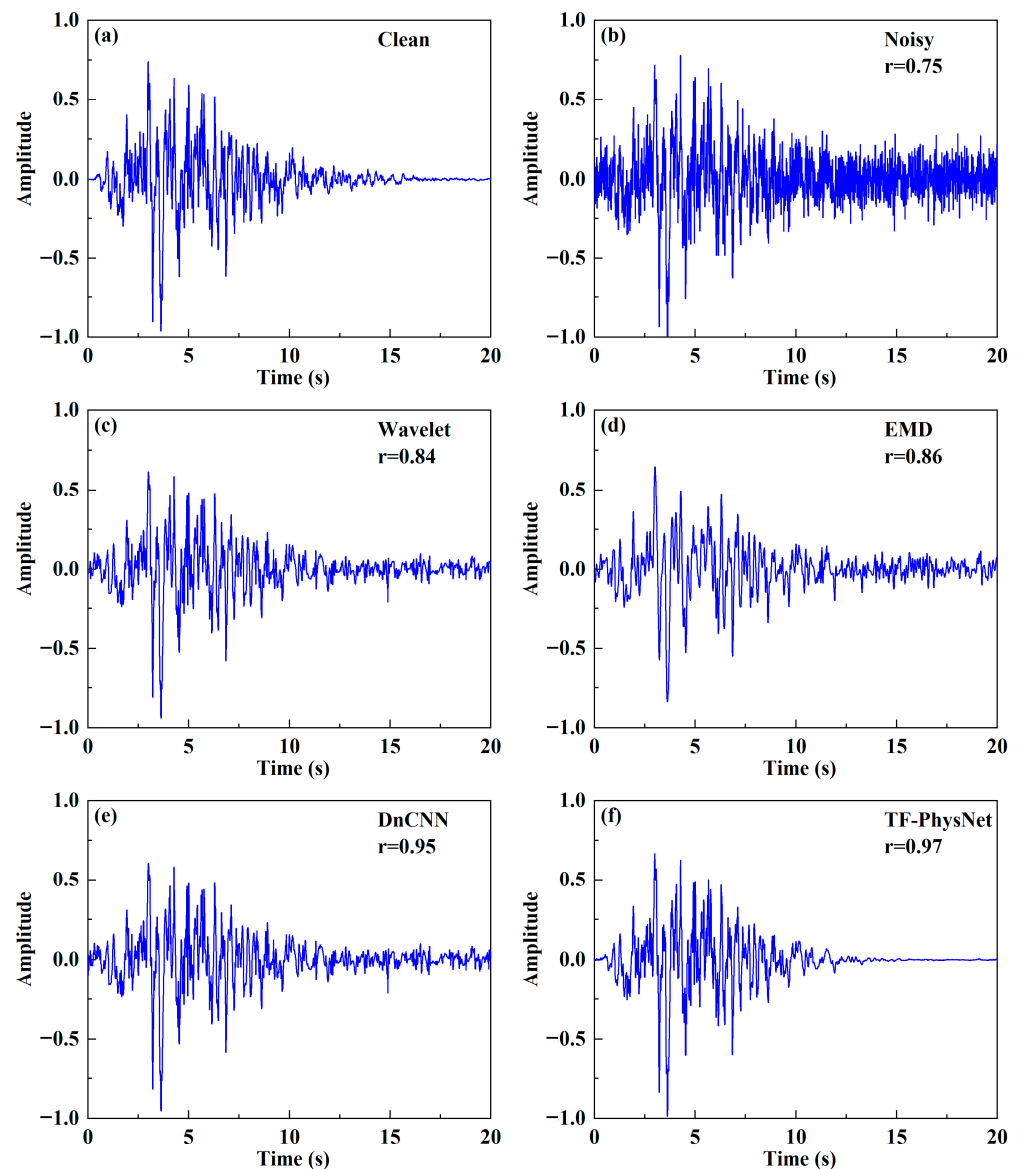


Figure 2. Time-domain waveforms of denoised synthetic seismic signals. (a) Clean seismic data; (b) Noisy seismic data; (c) Wavelet denoising result; (d) EMD denoising result; (e) DnCNN denoising result; and (f) TF-PhysNet denoising result.

By comparison, the waveform recovered by TF-PhysNet shows the closest agreement with the clean reference signal. Both the peak amplitudes and the overall waveform morphology are largely preserved, while unwanted noise components are effectively removed. Distinct seismic phases remain clearly identifiable, and the corresponding signal envelope appears smoother and more continuous. From this standpoint, these results suggest that TF-PhysNet strikes a more favorable balance between noise reduction and waveform fidelity under severe noise conditions, enabling effective denoising without sacrificing essential seismic information.

Evaluating performance solely in the time domain, however, does not fully capture the advantages of the proposed method. For this reason, the frequency-domain responses of different denoising techniques are further examined in Figure 3. In the noisy input signals, spectral energy is spread across a broad frequency range, with high-frequency components largely dominated by noise. After denoising, TF-PhysNet succeeds in concentrating the spectral energy within physically meaningful frequency bands while markedly suppressing high-frequency noise. In contrast, both the wavelet-based method and the DnCNN

approach are able to approximate the true signal spectrum at low frequencies but continue to retain a noticeable amount of noise in the high-frequency range. In contrast, the EMD method largely removes high-frequency noise but does so at the expense of excessively attenuating substantial portions of the true signal spectrum. Among all the compared methods, only TF-PhysNet is able to simultaneously restore the clean signal spectrum with high fidelity and suppress high-frequency noise effectively.

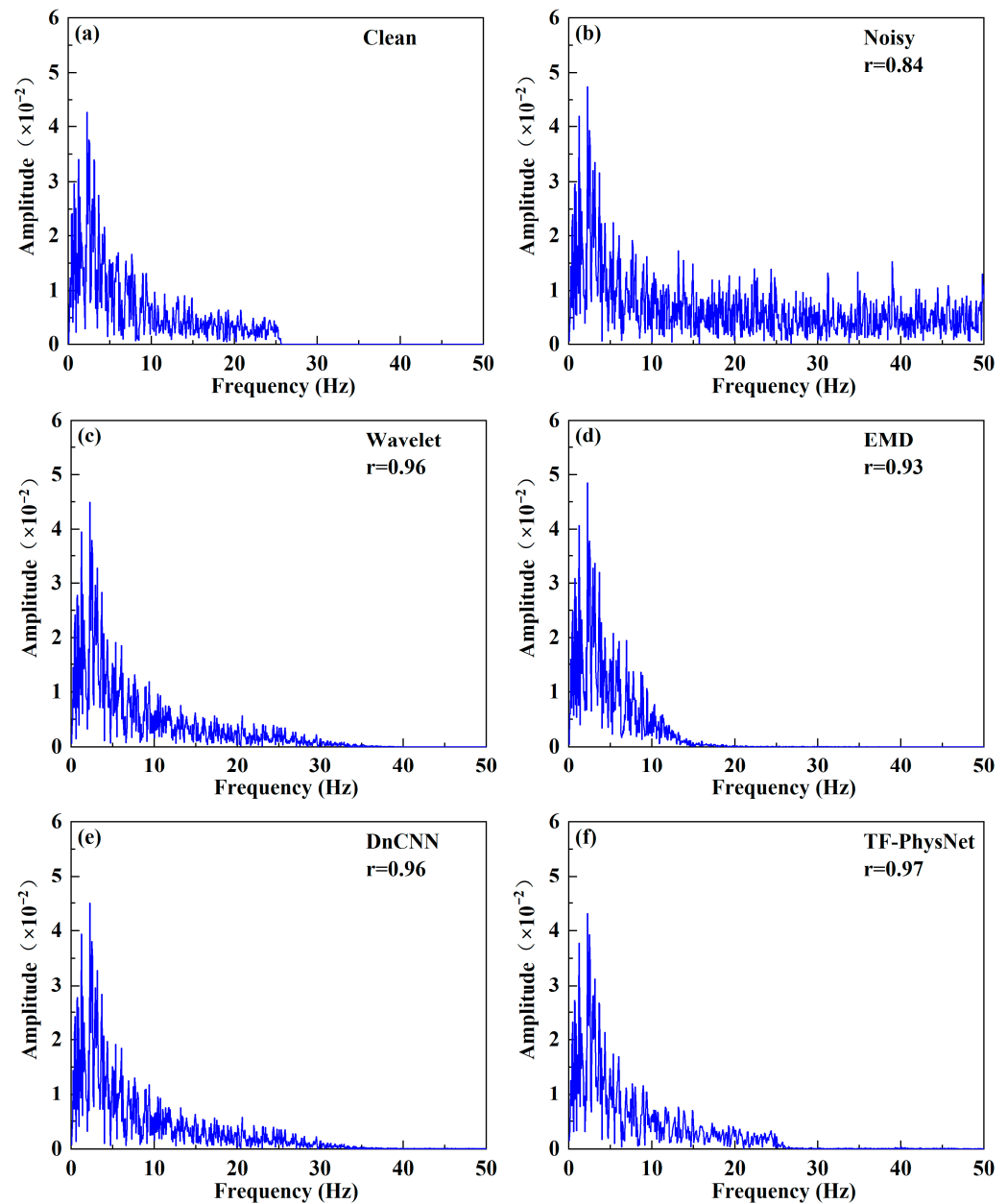


Figure 3. Amplitude spectrum of denoised synthetic seismic signals. (a) Clean seismic data; (b) Noisy seismic data; (c) Wavelet denoising result; (d) EMD denoising result; (e) DnCNN denoising result; and (f) TF-PhysNet denoising result.

Figure 4 compares the peak ground acceleration (PGA) values of clean seismic signals with those obtained after denoising using different methods. As shown in Figure 4a–c, the conventional wavelet- and EMD-based methods display considerable scatter around the 1:1 reference line, most notably within the low- and mid-PGA intervals. This dispersion suggests that peak amplitudes are not fully preserved during denoising. The DnCNN-based method exhibits improved consistency, with a larger proportion of points clustered closer

to the reference line, underscoring the benefit of deep learning for noise suppression while maintaining the overall amplitude trend. That said, minor deviations from the ideal linear relationship are still evident, which can reasonably be attributed to over-smoothing effects that weaken localized peak amplitudes.

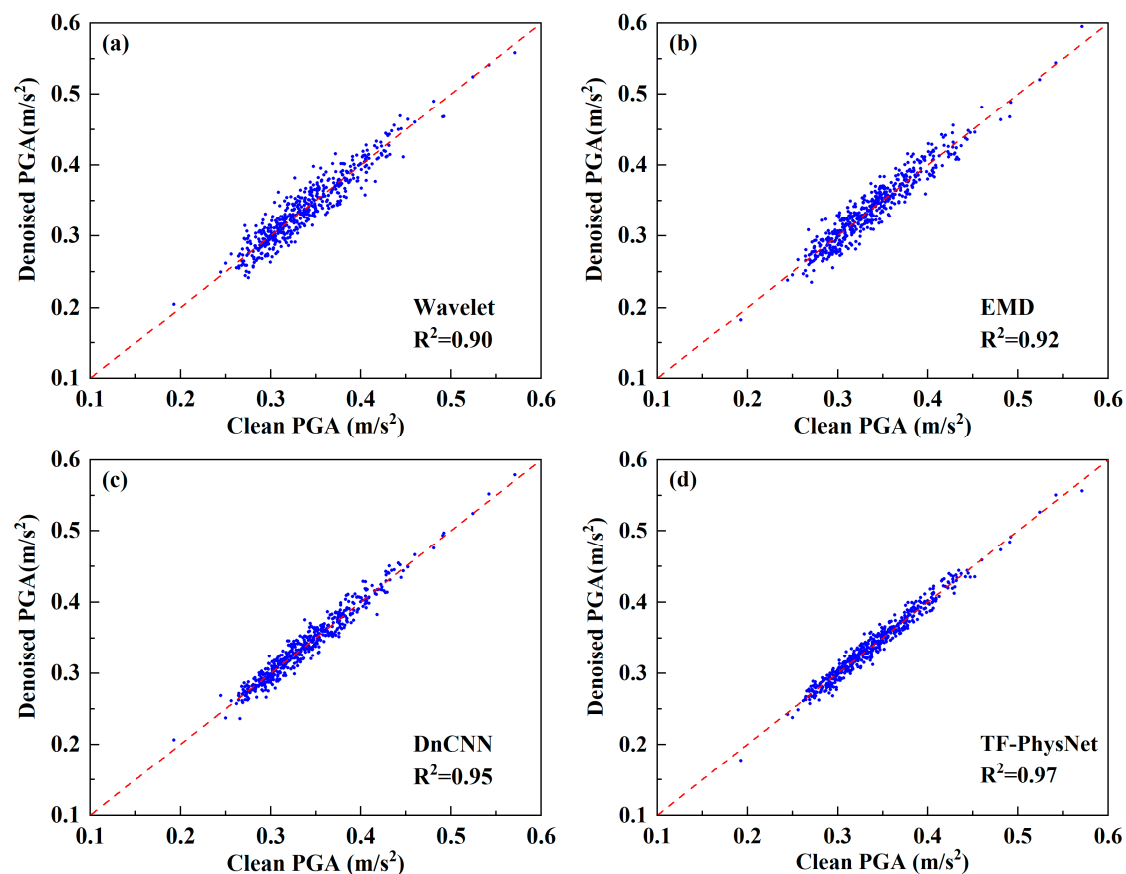


Figure 4. Distribution of clean and denoised peak ground acceleration (PGA) for different methods using synthetic seismic signals. (a) Wavelet method; (b) EMD method; (c) DnCNN method; and (d) TF-PhysNet method.

The proposed TF-PhysNet, as shown in Figure 4d, demonstrates the best performance among all the compared methods. The scatter points are tightly clustered along the 1:1 reference line across the entire PGA dynamic range, resulting in the highest R^2 value. From this standpoint, the results indicate that TF-PhysNet not only suppresses noise effectively but also preserves peak ground motion characteristics with high fidelity, demonstrating superior robustness and amplitude consistency in seismic signal denoising.

Figure 5 further compares the quantitative denoising performance of the different methods under varying input SNR levels. All methods exhibit consistent performance trends as the noise level varies. Specifically, a higher input SNR results in an increased output SNR and r , accompanied by corresponding reductions in MSE and RMSE. These patterns reflect gradual improvements in both denoising effectiveness and reconstruction accuracy.

Obvious performance differences can be observed among the compared approaches. Traditional wavelet- and EMD-based methods exhibit limited denoising capability under low-SNR conditions, where dominant noise interference severely obscures the underlying seismic signals. In such cases, these methods achieve only modest output SNR improvements, while reconstruction errors remain relatively high, indicating limited robustness under severe noise conditions. The DnCNN-based approach offers noticeable improve-

ments across the full SNR range, achieving higher output SNR values, stronger waveform correlation, and reduced error metrics. Nevertheless, TF-PhysNet consistently delivers the best overall results. Its advantage is particularly evident at low and intermediate input SNRs, where it more accurately recovers seismic signals and better preserves key waveform features.

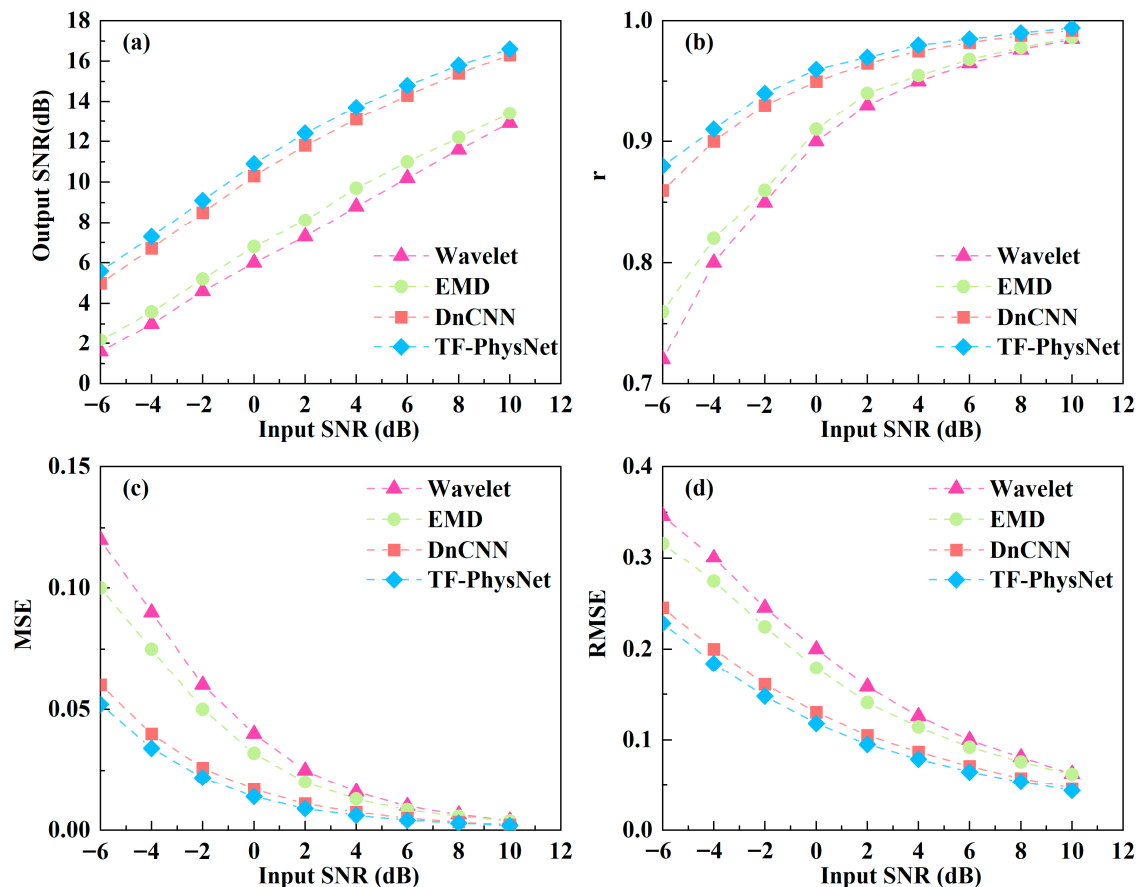


Figure 5. Quantitative performance comparison on synthetic seismic signals with varying input SNRs. (a) Output SNR; (b) correlation coefficient (r); (c) mean squared error (MSE); and (d) root mean squared error (RMSE).

Table 1 summarizes the denoising results obtained for synthetic seismic data. At low input SNRs, deep learning-based approaches clearly outperform traditional methods. When the input SNR is -6 dB, TF-PhysNet attains an output SNR of 5.6 dB, corresponding to improvements of approximately 250% and 155% over the wavelet- and EMD-based methods, respectively. Even relative to DnCNN, TF-PhysNet achieves an additional SNR gain of about 12%, highlighting its enhanced noise suppression capability under severely noisy conditions.

Performance differences are also evident in terms of r . Under the most challenging condition, TF-PhysNet achieves a value of $r = 0.88$. This corresponds to relative improvements of approximately 22% and 16% over the wavelet-based and EMD-based methods, as well as a noticeable gain over DnCNN. As the input SNR increases, the values of r for all methods improve accordingly; notably, TF-PhysNet consistently maintains the highest r across all SNR levels.

Table 1. Denoising results for synthetic seismic dataset across input SNR levels.

Wavelet			EMD		DnCNN		TF-PhysNet	
Input SNR (dB)	Output SNR (dB)	r	Output SNR (dB)	r	Output SNR (dB)	r	Output SNR (dB)	r
−6	1.6	0.72	2.2	0.76	5.0	0.86	5.6	0.88
−4	3.0	0.80	3.6	0.82	6.7	0.90	7.3	0.91
−2	4.6	0.85	5.2	0.86	8.5	0.93	9.1	0.94
0	6.0	0.90	6.8	0.91	10.3	0.95	10.9	0.96
2	7.3	0.93	8.1	0.94	11.8	0.965	12.4	0.970
4	8.8	0.95	9.7	0.955	13.1	0.975	13.7	0.980
6	10.2	0.965	11.0	0.968	14.3	0.982	14.8	0.985
8	11.6	0.976	12.2	0.978	15.4	0.988	15.8	0.990
10	12.9	0.985	13.4	0.986	16.3	0.992	16.6	0.994

5. Experiments on Real Seismic Dataset

Following validation on synthetic seismic datasets, the proposed TF-PhysNet is further examined using real seismic records to assess its accuracy and practical applicability. Real-world seismic data, often affected by complex and strongly nonstationary noise, constitute a more demanding test scenario. Accordingly, this part of the analysis emphasizes the capability of TF-PhysNet to preserve waveform continuity, suppress artificial artifacts, and maintain the stability of engineering-relevant parameters under realistic conditions.

Figure 6 illustrates the time-domain denoising results for real seismic records obtained with different methods. The original noisy waveform exhibits pronounced amplitude fluctuations and irregular high-frequency components, which obscure seismic phase arrivals and interrupt temporal continuity. For this reason, qualitative inspection of waveform morphology and continuity provides an important complement to quantitative metrics when evaluating denoising performance.

The wavelet-based approach removes part of the high-frequency noise; however, residual oscillations remain evident, particularly in the later portions of the signal, suggesting incomplete noise suppression. The EMD-based method produces a comparatively smoother waveform but introduces localized amplitude distortions that may affect the consistency of seismic phase characteristics. The DnCNN-based approach achieves stronger overall noise attenuation; nevertheless, noticeable over-smoothing occurs near abrupt waveform transitions, leading to reduced contrast and the loss of localized signal features.

By contrast, the waveform denoised using TF-PhysNet shows improved temporal continuity with substantially fewer artificial oscillations. Seismic phase arrivals appear more coherent, and weak signal components are better retained without generating spurious structures. From this standpoint, these observations indicate that the proposed method achieves a more balanced compromise between effective noise reduction and faithful waveform preservation under realistic noise conditions.

Figure 7 further compares the frequency-domain spectra of the noisy input and the denoised outputs produced by different methods. In the noisy signal, spectral energy is broadly distributed across both low- and high-frequency bands, with useful signal components heavily entangled with noise. Such spectral characteristics make signal interpretation particularly difficult, especially in frequency ranges dominated by noise.

Conventional denoising techniques tend to suppress part of the high-frequency energy, which at first glance results in a visible reduction in background noise. Yet this process is often accompanied by an unintended attenuation within frequency bands that contain the dominant components of the target signal. Consequently, energy loss occurs in critical spec-

tral regions, and a noticeable spectral decay emerges around the signal-related frequencies. From this standpoint, such behavior reveals a strong sensitivity to parameter selection and suggests that essential signal features are frequently eliminated along with the noise.

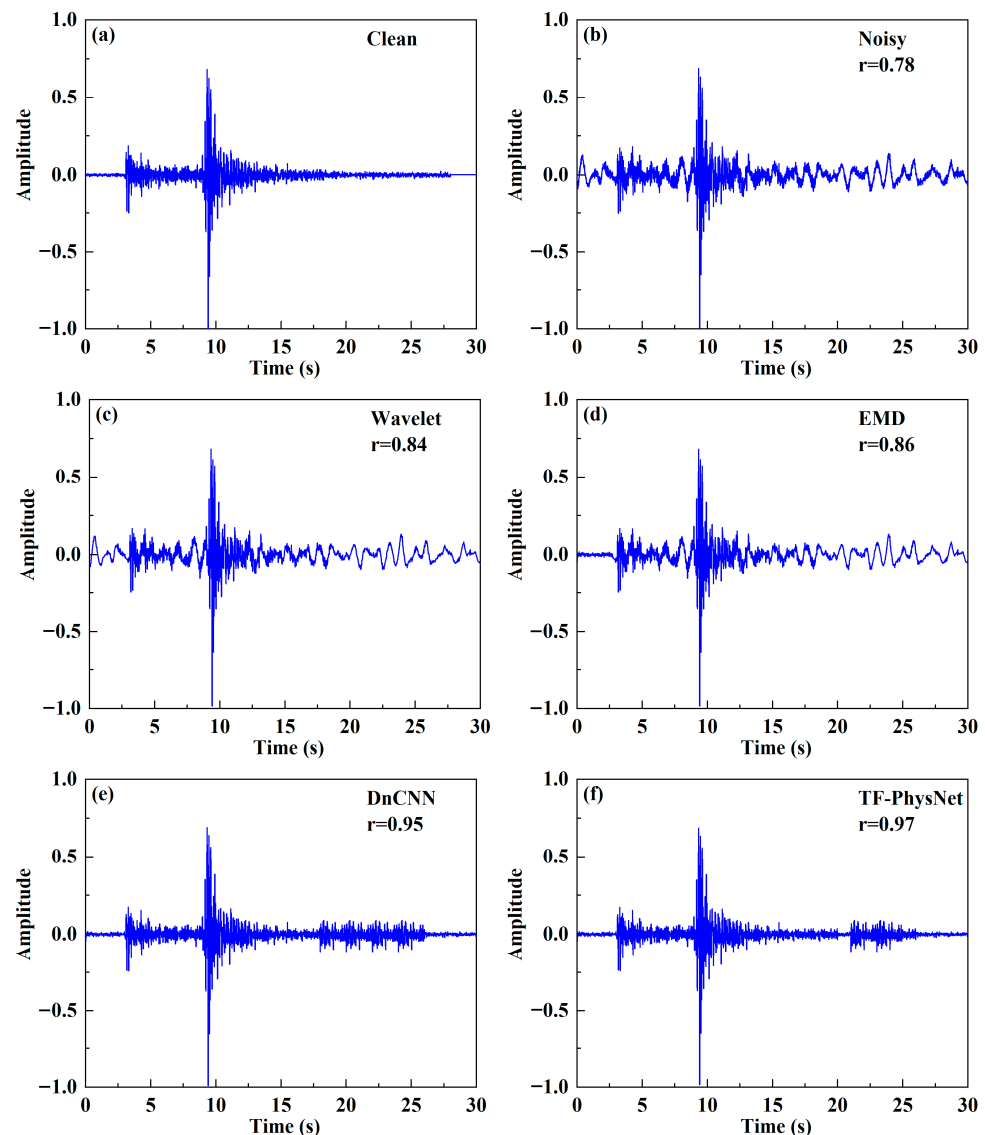


Figure 6. Time-domain waveforms of denoised real seismic signals. (a) Clean seismic data; (b) Noisy seismic data; (c) Wavelet denoising result; (d) EMD denoising result; (e) DnCNN denoising result; and (f) TF-PhysNet denoising result.

EMD-based methods and wavelet domain techniques provide a fair improvement in spectral enhancement. The energy gets more concentrated in the mid-frequency band, and the effect of random noise gets mitigated partially. The noise residual still persists around the dominant spectral components, especially in the regions where the signal strength is less. This effect indicates that there is no robustness in the case of complex spectral patterns of non-stationary noise. The TF-PhysNet approach results in an orderly arrangement of the spectral components. The major spectral components of the signal are still distinguishable, whereas the background noise gets attenuated in the broad frequency band. The suppression of the high-frequency components does not cause any degradation in the signal-dominated spectral areas.

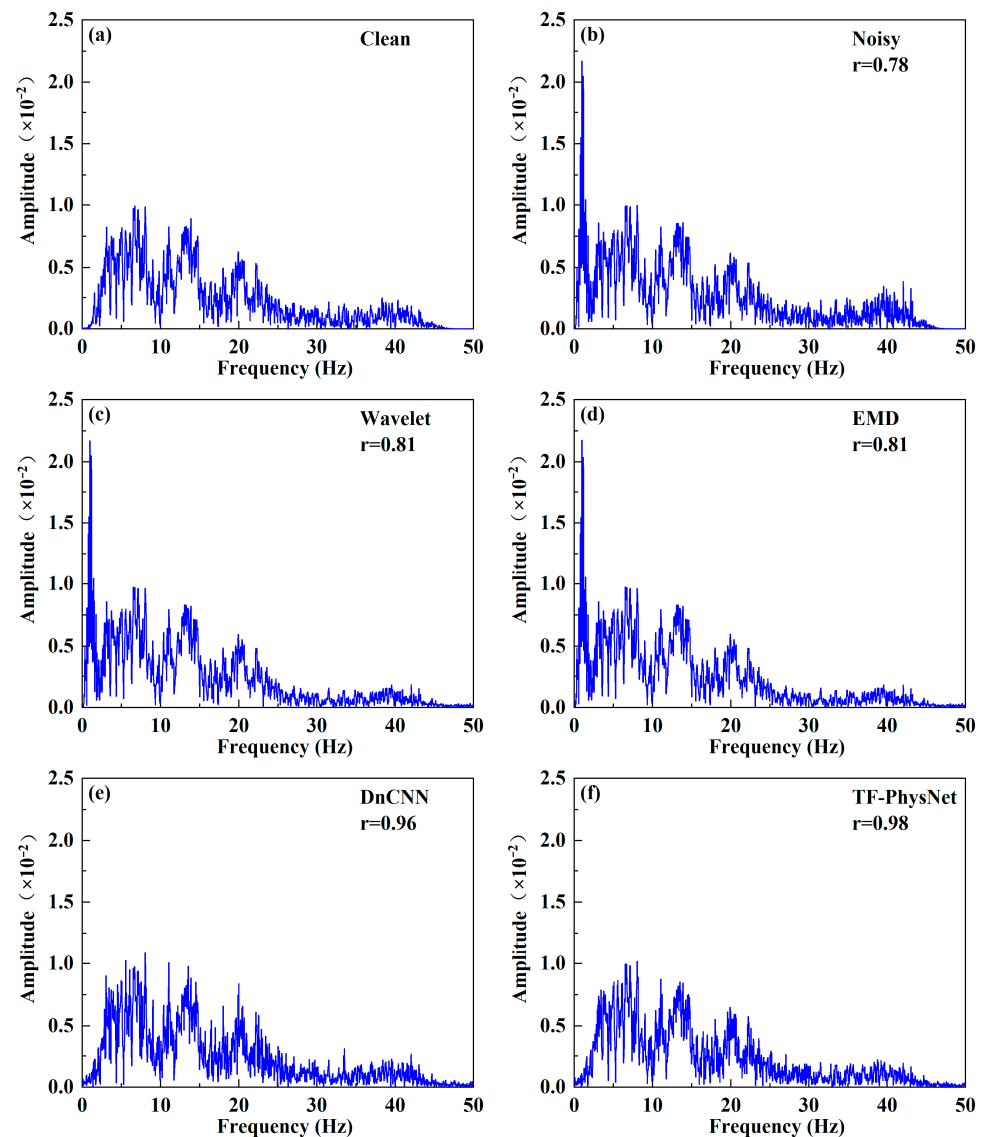


Figure 7. Amplitude spectrum of denoised real seismic signals. (a) Clean seismic data; (b) Noisy seismic data; (c) Wavelet denoising result; (d) EMD denoising result; (e) DnCNN denoising result; and (f) TF-PhysNet denoising result.

Figure 8 shows the scatter distributions of PGA values obtained from denoised real seismic records using different methods. Pronounced dispersion is observed for the wavelet- and EMD-based approaches, indicating a strong sensitivity of PGA estimation to residual noise and localized waveform distortions. The DnCNN-based method reduces the overall spread of PGA values; however, systematic deviations in certain amplitude ranges are still evident, suggesting potential bias introduced by over-smoothing effects. In contrast, PGA estimates obtained using TF-PhysNet display a more compact and uniformly distributed pattern across the full amplitude range. This behavior points to enhanced stability and reliability in PGA estimation when the proposed method is applied to real seismic data affected by complex, nonstationary noise.

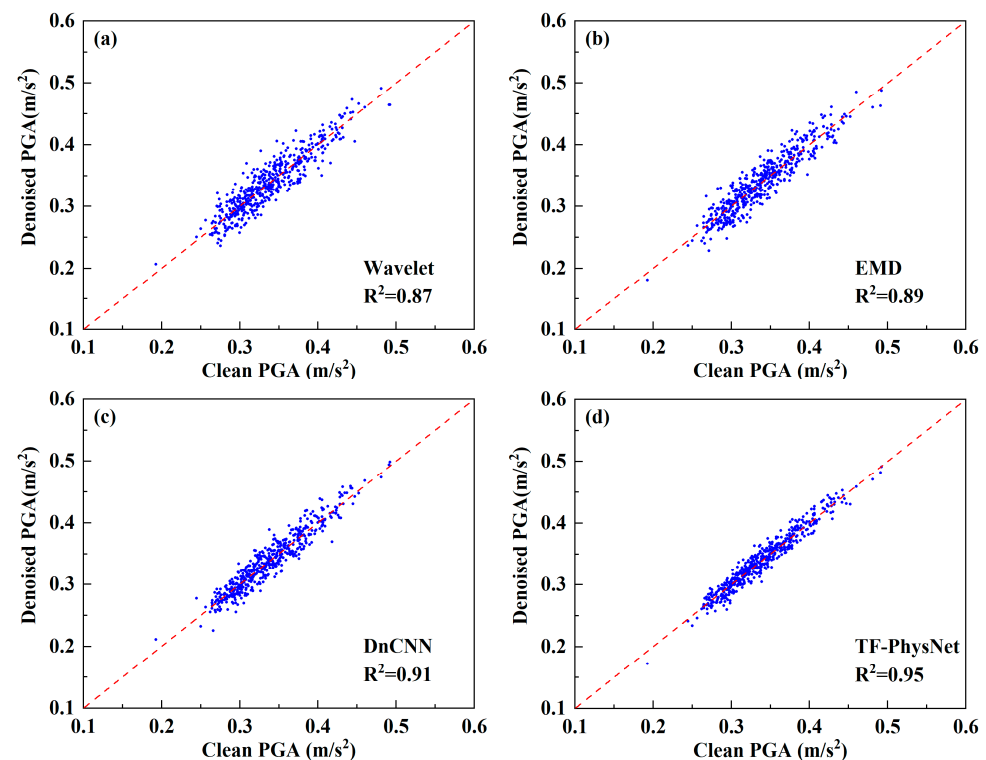


Figure 8. Distribution of clean and denoised peak ground acceleration (PGA) for different methods using real seismic signals. (a) Wavelet method; (b) EMD method; (c) DnCNN method; and (d) TF-PhysNet method.

For the wavelet- and EMD-based approaches, however, the denoised PGA values show relatively large dispersion around the 1:1 reference line. This effect is especially evident at lower PGA levels, where the recovered peak amplitudes tend to deviate noticeably from their clean counterparts. Such discrepancies imply that these traditional techniques may introduce amplitude bias during the denoising process, either as a consequence of residual high-frequency fluctuations or due to incomplete separation between signal and noise components. As a result, while the overall PGA trend is generally retained, the consistency of peak amplitude recovery remains limited, particularly for weak seismic events. By comparison, the results produced by the DnCNN- and TF-PhysNet-based methods exhibit much tighter clustering of scatter points along the reference line over the entire PGA range, indicating more accurate preservation of peak amplitudes after denoising. Notably, TF-PhysNet achieves the smallest dispersion and the closest agreement with the clean PGA values, reflecting stronger robustness in peak ground motion recovery. From this standpoint, its ability to suppress noise while preserving physically meaningful amplitude variations enables more reliable PGA estimation under realistic noise conditions, which is essential for seismic intensity evaluation and a broad range of engineering applications.

Figure 9 summarizes the quantitative performance of the four denoising approaches under varying experimental conditions. As data conditions become more favorable, the evaluation metrics increase accordingly for all methods. Both the wavelet- and EMD-based techniques follow similar upward trends, although their growth rates remain relatively modest across most intervals. The DnCNN-based approach consistently outperforms these traditional methods, with particularly pronounced improvements in the intermediate range of the control parameter. TF-PhysNet, however, maintains the highest performance throughout the entire range. Moreover, the performance gap between TF-PhysNet and the other approaches remains relatively stable as the control parameter increases, suggesting sustained and systematic improvement rather than isolated gains at specific operating points.

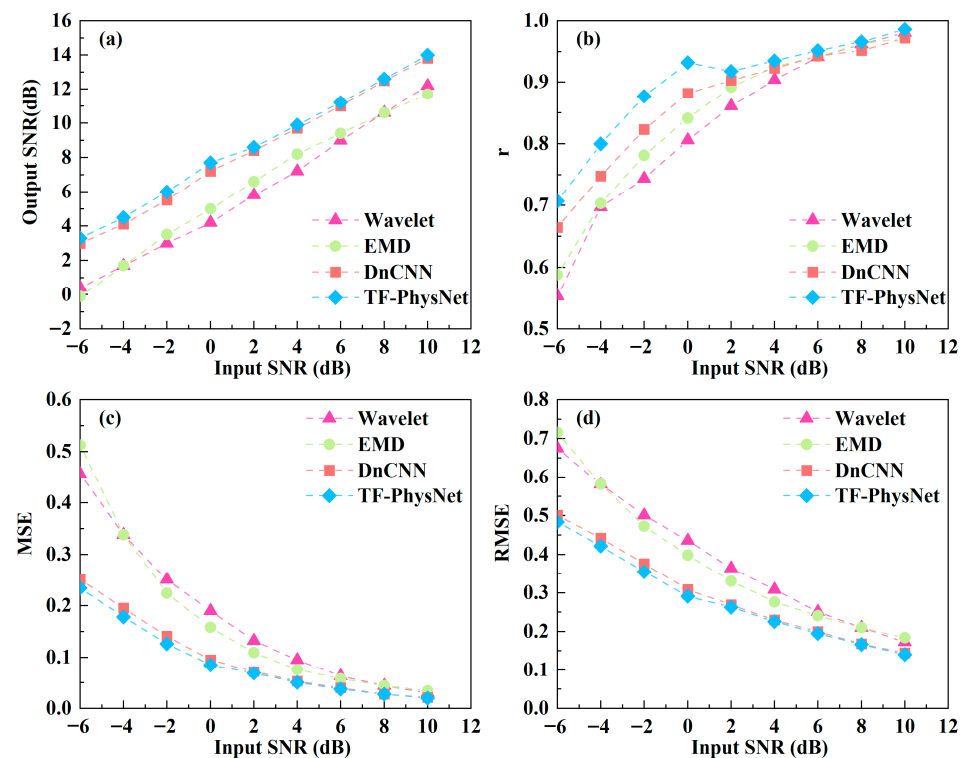


Figure 9. Quantitative performance comparison on real seismic signals with varying input SNRs. (a) Output SNR; (b) correlation coefficient (r); (c) mean squared error (MSE); and (d) root mean squared error (RMSE).

As the quality of the input data improves, all methods show an overall decline in error magnitude. That said, the pace at which errors decrease varies substantially across the different approaches. The wavelet- and EMD-based methods display only gradual reductions, with relatively large errors still present under less favorable conditions. The DnCNN-based approach achieves a faster reduction in error within the intermediate range; however, its error curve tends to level off as experimental conditions continue to improve. By contrast, TF-PhysNet consistently produces the lowest error values across most scenarios, with a smoothly evolving curve that avoids abrupt drops or oscillatory behavior.

Traditional denoising techniques also exhibit pronounced performance fluctuations over the full range of experimental conditions, with meaningful improvements confined to a relatively narrow interval. Learning-based methods, in comparison, demonstrate more stable and predictable behavior. Among these, TF-PhysNet maintains a persistently low error level across different settings, underscoring its robustness and reliability under varying data conditions. Such characteristics of the performance curves indicate a steadier balance between effective noise attenuation and faithful signal retention as data conditions vary.

Table 2 presents a quantitative comparison of denoising performance on real seismic data across a range of input SNR levels. At a very low input SNR of -6 dB, the wavelet-based and EMD-based methods yield output SNR values below 1 dB, indicating only marginal noise reduction. In contrast, TF-PhysNet achieves an output SNR of 3.3 dB, corresponding to improvements of more than 700% over the wavelet-based method and over 1000% relative to the EMD-based method. Under the same condition, TF-PhysNet attains a value of $r = 0.707$, corresponding to relative increases of approximately 28% and 20%, respectively.

Table 2. Denoising results for real seismic dataset across input SNR levels.

Wavelet			EMD		DnCNN		TF-PhysNet	
Input SNR (dB)	Output SNR (dB)	r	Output SNR (dB)	r	Output SNR (dB)	r	Output SNR (dB)	r
−6	0.4	0.553	−0.1	0.588	3.0	0.664	3.3	0.707
−4	1.7	0.697	1.7	0.703	4.1	0.748	4.5	0.800
−2	3.0	0.744	3.5	0.781	5.5	0.823	6.0	0.877
0	4.2	0.806	5.0	0.841	7.2	0.882	7.7	0.932
2	5.8	0.861	6.6	0.892	8.4	0.903	8.6	0.918
4	7.2	0.904	8.2	0.926	9.7	0.923	9.9	0.935
6	9.0	0.941	9.4	0.942	11.0	0.943	11.2	0.952
8	10.6	0.962	10.6	0.963	12.5	0.952	12.6	0.966
10	12.2	0.981	11.7	0.972	13.8	0.972	14.0	0.986

As the input SNR increases, the denoising performance of all methods improves; however, the relative advantage of TF-PhysNet remains consistent. At an input SNR of 0 dB, TF-PhysNet improves the output SNR by approximately 83% compared with the wavelet-based method and by 54% compared with EMD-based method, while achieving a value of r exceeding 0.93. Even at higher input SNR levels from 8 to 10 dB, TF-PhysNet continues to deliver the highest output SNR and r , indicating sustained performance gains rather than isolated improvements at specific noise levels.

Compared with DnCNN, TF-PhysNet exhibits more moderate yet systematic performance gains. Across the full SNR range, TF-PhysNet provides an additional output SNR improvement of approximately 3 to 10 percent while consistently achieving higher values of r , highlighting the benefit of integrating frequency-adaptive decomposition with physics-guided constraints beyond purely data-driven learning strategies.

6. Conclusions

This work proposes a time–frequency adaptive decomposition and physics-guided neural network framework for seismic data denoising. The proposed framework is designed to overcome the inherent shortcomings of both traditional signal processing schemes and purely data-driven deep learning models. Rather than relying solely on statistical fitting, it explicitly leverages the intrinsic time–frequency characteristics of seismic signals and embeds prior physical constraints into the learning procedure. From this standpoint, the model is able to attenuate noise effectively while retaining the essential morphology of seismic waveforms, a balance that is often difficult to achieve. The interplay between data features and physical guidance ultimately leads to enhanced robustness and more reliable denoising performance under complex and highly variable noise environments. The main conclusions are as follows:

(1) TF-PhysNet demonstrates strong noise suppression capability even in severely degraded scenarios. When the input SNR is −6 dB, the absolute value of the output SNR is still limited, as expected; nevertheless, the proposed approach yields an SNR improvement of 11.6 dB for synthetic seismic signals and approximately 9.3 dB for real seismic records. These gains consistently exceed those obtained by the baseline methods, indicating a clear advantage in handling extreme noise contamination.

(2) The physics-guided multi-term loss function effectively suppresses non-physical oscillations and enhances waveform similarity in seismic denoising. For synthetic seismic data, r consistently ranges from 0.88 to 0.994, while for real seismic records, r remains above 0.70 under severe noise conditions and increases steadily with improving signal quality.

(3) The robustness of TF-PhysNet is further confirmed across a broad spectrum of input SNR levels. Despite substantial fluctuations in the quality of the input signals, the recovered seismic traces consistently exhibit strong reconstruction capability. For real seismic data in particular, the output SNR can reach up to 14.0 dB, while the corresponding r increases to 0.986. This behavior highlights the stability and adaptability of the proposed method over a wide SNR range.

(4) In terms of reconstruction accuracy, the proposed approach also outperforms the comparison methods. Across all tested input SNR conditions, TF-PhysNet consistently produces lower MSE and RMSE values. Notably, when the input SNR is -6 dB, reconstruction errors are markedly reduced, underscoring the method's ability to achieve stable and accurate seismic signal reconstruction even under severe noise interference.

A full ablation study was not included in this paper in order to maintain a focused experimental scope; isolating the individual contribution of each module under identical conditions will be investigated in future work. Beyond its denoising performance, the proposed framework also demonstrates practical potential for seismic monitoring applications. In real-world scenarios, large volumes of seismic data are continuously recorded from distributed stations, where reliable identification of weak or hazardous events under low-SNR conditions is essential. By enhancing waveform clarity and preserving phase consistency, TF-PhysNet can improve the robustness of automatic event detection and support early-warning and hazard assessment systems. Moreover, the combination of adaptive time–frequency decomposition and physics-guided constraints provides a flexible foundation for future extensions to multi-station or multi-component datasets and integration into real-time monitoring pipelines, contributing to more reliable data-driven seismic analysis frameworks.

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Data Availability Statement: The source code developed in this study for TF-PhysNet, including preprocessing, adaptive frequency decomposition, physics-guided constraints, model training, and evaluation scripts, is publicly available on GitHub at: <https://github.com/zqh3030/TF-PhysNet.git> (accessed on 15 February 2026). The repository includes scripts to reproduce the main experiments and quantitative results reported in this paper. The real seismic data used in this study are obtained from the publicly available STEAD dataset: <https://github.com/smousavi05/STEAD>. (accessed on 15 February 2026). The dataset description is available at <https://doi.org/10.1109/ACCESS.2019.2947848>. Synthetic data are generated using scripts included in the repository.

Conflicts of Interest: Author Miantao Zhang was employed by Construction Administration Bureau of Central Yunnan Water Diversion Project. Author Yanjie Zhang was employed by the company Yunnan Dianzhong Water Diversion Engineering Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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