

Article

Automatic Reconstruction of Velocity and Displacement from Seismic Acceleration Measurements by a Cycle-Consistent Generative Adversarial Network

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Abstract

The reconstruction of velocity and displacement from acceleration measurements is essential for seismic or microseismic data interpretation. Many existing approaches produce excellent results in both velocity and displacement reconstruction. However, these reconstruction approaches involve a large number of parameters, which must be tuned for different datasets. There is room for improvement in high-precision and immediate reconstruction, particularly for large and noisy datasets. Therefore, we propose a deep learning approach that is parameter-free during inference to automatically reconstruct velocity and displacement from seismic acceleration measurements via a cycle-consistent generative adversarial network (CycleGAN). To obtain paired training data, we use a semi-synthetic method to prepare the dataset. Based on the dataset, we use CycleGAN to train two mapping functions for reconstructing the velocity and displacement from acceleration measurements. We then compare this method with two traditional methods on the test set. For the reconstruction of seismic velocity measurements, the mean average peak error (*Erp*), average deviation error (*Err*), and root-mean-square error (*Ers*) on the test set for the method proposed in this paper are 0.1478, 1.2269, and 0.0097, respectively. Moreover, for the reconstruction of seismic displacement measurements, the mean *Erp*, *Err*, and *Ers* values on the test set for the method proposed in this paper are 0.2004, 0.9783, and 5.6×10^{-4} , respectively. Additionally, under noisy input conditions, the records reconstructed by our approach exhibit the smallest degradation in signal-to-noise ratio (SNR) and preserve more records in the higher SNR range than those reconstructed by traditional methods. The results show that the proposed method achieves comparable accuracy in velocity reconstruction and better accuracy in displacement reconstruction than traditional methods. More importantly, it can automatically reconstruct records and remain robust to input noise without manual parameter tuning, demonstrating good prospects for practical application.

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Keywords: seismic signal; microseismic activities; data processing; automatic reconstruction; deep learning; CycleGAN

1. Introduction

Work considering the reconstruction of velocity and displacement from seismic acceleration measurements has a rich background. The acquisition of vibration signals by seismometers/geophones for analysis is the basis for understanding earthquakes. Seismic/microseismic displacement and velocity measurements play important fundamental roles in seismology; they can be utilized in source parameter calculation [1–6], geological hazard evaluation, and so on [7–10]. However, because of limitations in technical specifications and working conditions, most measured seismic or microseismic records are acceleration measurements, and it is therefore necessary to reconstruct velocity and displacement from acceleration measurements [11].

A significant number of methods have been proposed for reconstructing displacement or velocity from acceleration measurements [12]. The integration of measured acceleration has become a popular approach to obtaining unknown velocity and displacement [13]. Several mathematical methods were reported in the early literature, such as the trapezoid formula, Simpson's rule, the Newton–Cotes formula, and the Runge–Kutta algorithm. However, these methods are not exclusive to seismic/microseismic records and cannot solve this reconstruction problem perfectly. Therefore, many scholars have proposed reliable time-domain integration and frequency-domain conversion methods for this reconstruction problem. For time-domain integration methods, Chawla et al. [14] proposed a reconstruction approach based on non-dissipative time-integration schemes for the linear advection equation. Kim J. et al. [15] proposed autonomous dynamic displacement estimation using data fusion of acceleration and intermittent displacement measurements. Regarding frequency-domain conversion methods, Zhu et al. [16] proposed a low-frequency attenuation (LFA) algorithm, in which the integration of acceleration is conducted directly in the frequency domain. Hong and Lee et al. [12,17–19] proposed a set of approaches for reconstructing displacement from acceleration measurements by converting the initial value problem to a boundary value problem. Based on the work of Hong et al., Tezcan et al. [20] proposed a kernel-based alternative to the regularization scheme. The proposed method uses the least squares support vector machine (LSSVM) to solve the problem in a kernel-induced feature space. Finally, many approaches have been proposed and used to decompose the signal and remove the trend term, such as the Hilbert–Huang transform [21], wavelet transforms [22], and empirical mode decomposition [13].

Many of the above-mentioned reconstruction methods have suitable applications in displacement and velocity reconstruction. However, there are some limitations in the fast and accurate reconstruction of displacement and velocity, particularly for noisy acceleration data. Moreover, many of these methods require additional parameters and need to be adjusted according to different datasets. Furthermore, our research aims to reduce the number of parameters and thus the complexity, as we feel that having too many parameters to set is a considerable barrier to the application of automatic reconstruction methods.

Therefore, we propose an automated approach for reconstructing velocity and displacement from seismic acceleration measurements using a cycle-consistent generative adversarial network (CycleGAN). We use the powerful learning ability of CycleGAN to construct a function mapping from an acceleration dataset to a displacement or velocity dataset that remains robust to noise, thereby enhancing reconstruction accuracy. Furthermore, once we have constructed this function mapping, we can use it without setting or adjusting any parameters. Since our approach is parameter-free during inference, it can quickly, accurately, and automatically reconstruct displacement and velocity from acceleration measurements in industrial scenarios. Additionally, the elements in the datasets used to train CycleGAN do not need a one-to-one correspondence, which increases the practicability of our approach.

2. Materials and Methods

2.1. Dataset

In this study, two datasets were used: microseismic records generated during actual mining production activities and natural seismic records collected by seismic stations.

The microseismic records came from the microseismic monitoring system (shown in Figure 1) in the Huangtupo Copper and Zinc Mine, China. We consulted a microseismic record catalog from the Huangtupo Copper and Zinc Mine and obtained a dataset containing 9500 microseismic records of activity that occurred between September 1, 2019, and November 14, 2020 [23–25]. There are unavoidable differences between natural seismic records and mining-induced microseismic records, such as sampling rate and amplitude. Therefore, we separately created another dataset containing 9500 natural seismic records. These natural seismic records were obtained from the Center for Engineering Strong Motion Data (CESMD) and are available at www.strongmotioncenter.org.

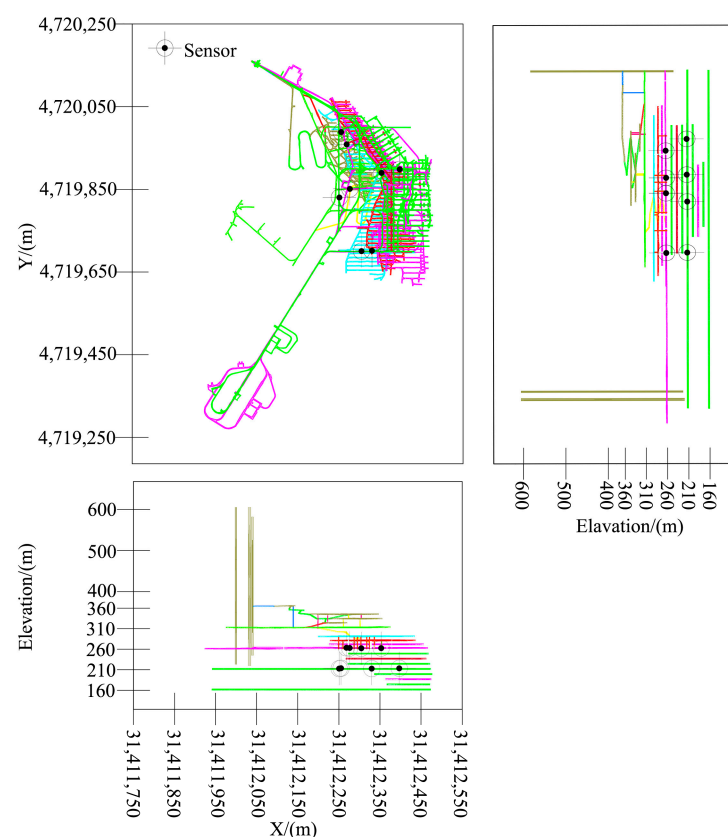


Figure 1. The microseismic system at the Huangtupo Copper and Zinc Mine consists of eight single-component accelerometers for continuous monitoring.

2.2. Cycle-Consistent Generative Adversarial Networks

In this paper, we mainly implement the reconstruction of velocity and displacement by building a cycle-consistent generative adversarial network (CycleGAN) that meets the needs of the application. CycleGAN is an efficient and successful type of generative adversarial network (GAN). Artificial intelligence methods are already being used in seismology [26–28]. Over the last few years, GANs have been one of the most efficient approaches for unsupervised deep learning on intricate distributions [29–34]. As shown in Figure 2, the GAN model generates excellent output through the mutual learning of two modules: a generator and a discriminator. The generator is a generative network that generates a fake object. It receives random noise z and generates fake objects, denoted as $G(z)$.

The discriminator is a discriminative network that ascertains whether the objects are real or fake. The input of the discriminator is an object x , and the output of the discriminator is $D(x)$, which represents the probability that x is a real object. If $D(x) = 1$, the input x is identified as a real object, whereas if $D(x) = 0$, the input x is identified as a fake object. During training, the generator aims to generate objects that are as realistic as possible to deceive the discriminator. The discriminator aims to distinguish the objects generated by the generator from real objects as accurately as possible. In this way, the generator and the discriminator constitute a dynamic game process. In an ideal state, the generator can generate an object $G(z)$ that is sufficiently realistic that the discriminator cannot determine whether it is real or fake, resulting in $D(G(z)) = 0.5$.

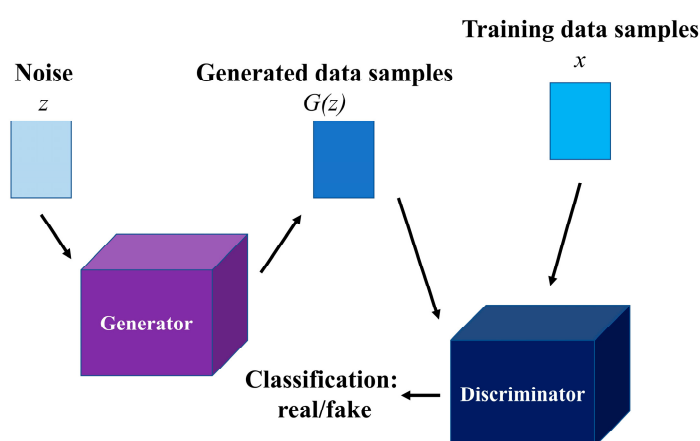


Figure 2. Architecture of a generative adversarial network (GAN). A GAN is a deep learning model that can produce output through mutual game learning between the generator and discriminator in the framework.

However, GANs have many limitations in their application, e.g., the input is random, the training data must be paired, and the output has no functional relationship with the input. Therefore, Zhu J.Y. et al. [35] proposed CycleGAN, which provides a new approach for learning to translate an image from a source domain X to a target domain Y using unpaired examples.

As shown in Figure 3, CycleGAN contains four modules: Generator A2B, Generator B2A, Discriminator A, and Discriminator B. The purpose of CycleGAN is to build the mapping functions between two given training samples $\{x_i \in X\}_{i=1}^N$ and $\{y_j \in Y\}_{j=1}^M$. Real_A and Real_B in Figure 3 are individual instances of X and Y , respectively. Mathematically, two generators can be described as two mapping functions, $G: X \rightarrow Y$ (Generator A2B) and $F: Y \rightarrow X$ (Generator B2A), with two associated adversarial discriminators D_Y (Discriminator B) and D_X (Discriminator A). The ability of CycleGAN to learn comes primarily from adversarial losses and cycle consistency losses.

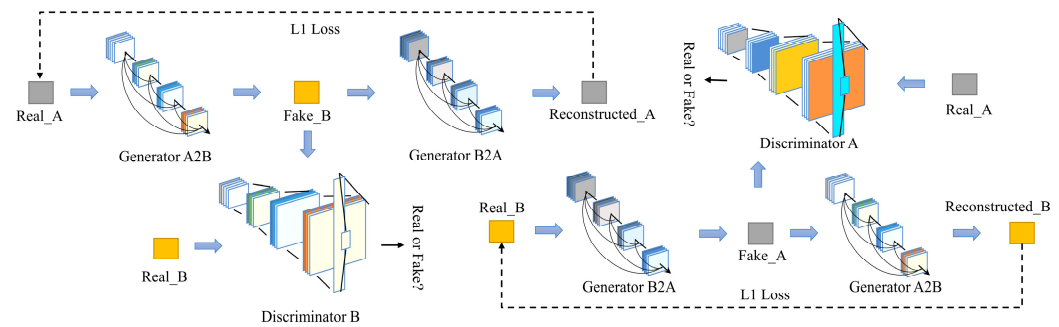


Figure 3. Architecture of the cycle-consistent generative adversarial network (CycleGAN). CycleGAN contains four modules: Generator A2B, Generator B2A, Discriminator A, and Discriminator B. The ability of CycleGAN to learn comes primarily from adversarial losses and cycle consistency losses.

Adversarial losses make the generated object distribution closer to the target object. For the mapping function $G: X \rightarrow Y$ and its discriminator D_Y , the adversarial loss can be expressed as

$$L_{GAN}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{data}(y)} [\log(D_Y(y))] + \mathbb{E}_{x \sim p_{data}(x)} [\log(1 - D_Y(G(x)))] \quad (1)$$

where Generator A2B generates Fake_B, which looks similar to Real_B, but Discriminator B tries to distinguish them, i.e.,

$$\min_G \max_{D_Y} L_{GAN}(G, D_Y, X, Y). \quad (2)$$

The same applies to Generator B2A and Discriminator A, i.e.,

$$\min_F \max_{D_X} L_{GAN}(F, D_X, Y, X). \quad (3)$$

In order to ensure that the primary information from which the object originated is retained during the conversion process, the whole deep learning model should be cycle-consistent, i.e.,

$$x \rightarrow G(x) \rightarrow F(G(x)) \approx x, \quad (4)$$

$$y \rightarrow F(y) \rightarrow G(F(y)) \approx y. \quad (5)$$

Cycle-consistency losses are used to carry out the above ideas and are calculated by the following formula:

$$L_{cyc}(G, F) = \mathbb{E}_{x \sim p_{data}(x)} [\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim p_{data}(y)} [\|G(F(y)) - y\|_1]. \quad (6)$$

The full objective of CycleGAN is

$$L(G, F, D_X, D_Y) = L_{GAN}(G, D_Y, X, Y) + L_{GAN}(F, D_X, Y, X) + \lambda L_{cyc}(G, F), \quad (7)$$

where λ controls the relative importance of the two objectives. The ultimate goal of this model after training is

$$G^*, F^* = \arg \min_{G, F} \max_{D_X, D_Y} L(G, F, D_X, D_Y). \quad (8)$$

Finally, CycleGAN can learn to automatically form a mapping function that allows objects in the two target domains to be converted into each other.

In the context of our specific seismic reconstruction task, the source domain X represents the acquired acceleration measurements, while the target domain Y represents the desired velocity or displacement measurements, which is further detailed in Section 2.3.

2.3. Reconstruction Approach

Based on CycleGAN, we propose an approach for reconstructing displacement or velocity from seismic acceleration measurements. The proposed CycleGAN can directly reconstruct a one-dimensional waveform of displacement $S_d(t, f)$ or velocity $S_v(t, f)$ from a one-dimensional waveform of an acceleration measurement $S_a(t, f)$.

The recorded seismic acceleration measurement, defined as $Y_a(t, f)$, is the superposition of the signal, $S_a(t, f)$, and noise, $N_a(t, f)$ [36–38]:

$$Y_a(t, f) = S_a(t, f) + N_a(t, f). \quad (9)$$

The velocity measurement $\hat{Y}_v(t, f)$ and displacement measurement $\hat{Y}_d(t, f)$ generated by traditional reconstruction methods are superpositions of the signal and noise. However, we use CycleGAN to construct two mapping functions, $F_{a2v}(x)$ and $F_{a2d}(x)$, as follows:

$$\hat{S}_v(t, f) = \hat{Y}_v(t, f) - \hat{N}_v(t, f) = F_{a2v}(Y_a(t, f)), \quad (10)$$

$$\hat{S}_d(t, f) = \hat{Y}_d(t, f) - \hat{N}_d(t, f) = F_{a2d}(Y_a(t, f)). \quad (11)$$

This means that the reconstructed velocity and displacement measurements are robust to the noise contained in the input acceleration measurement.

Specifically, we design the network structure and parameters of CycleGAN, as shown in Figure 4, to construct the mapping functions $F_{a2v}(x)$ and $F_{a2d}(x)$. The network's principal components are one-dimensional convolution (Conv1d), one-dimensional instance normalization (InstanceNorm1d), one-dimensional transposed convolution (ConvTranspose1d), and residual blocks. This approach comprises two residual networks (ResNets) and two convolutional neural networks (CNNs) for reconstructing displacement and velocity from acceleration measurements. Through training on the dataset, our CycleGAN model automatically adjusts the network parameters so that the reconstructed velocity or displacement is sufficiently accurate.

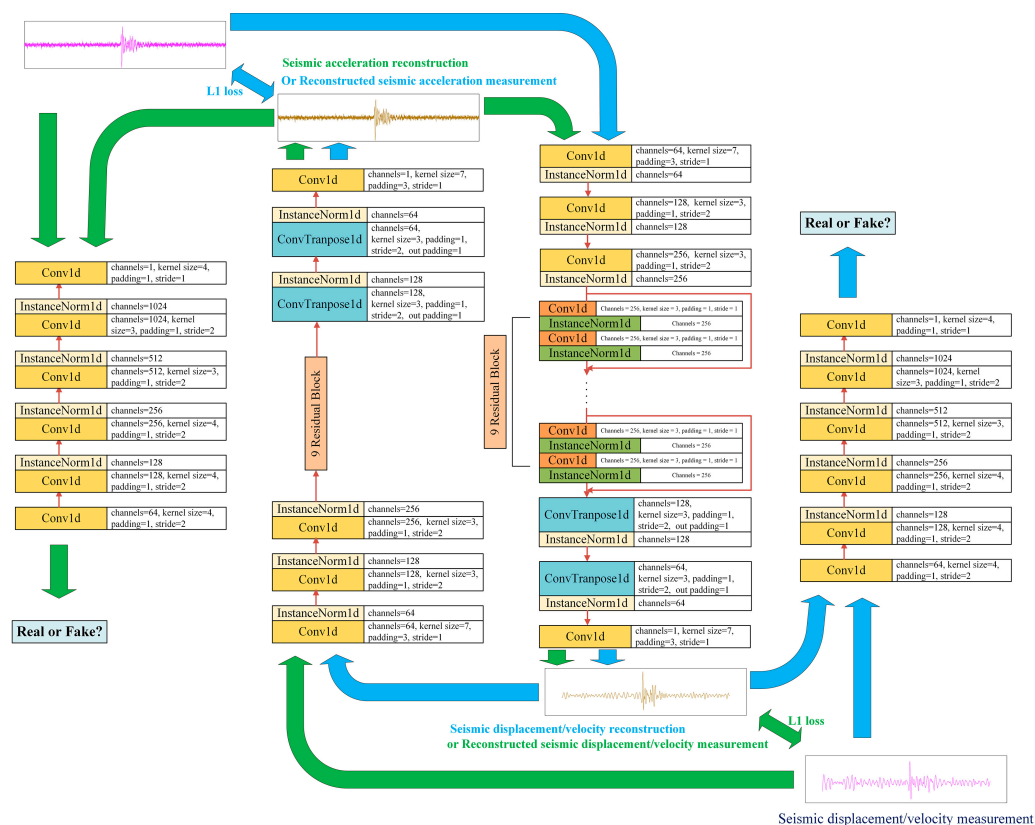


Figure 4. Network structure and parameters of CycleGAN, designed to construct mapping functions $F_{a2v}(x)$ and $F_{a2d}(x)$. After training on the dataset, we can use $F_{a2v}(x)$ and $F_{a2d}(x)$ to reconstruct the velocity and displacement while remaining robust to noise. There is no need to set any parameters during the reconstruction process.

3. Results

In this section, we train and test our approach on microseismic and seismic datasets. Furthermore, we compare our approach with some commonly used traditional methods.

3.1. Experiment Based on Mining-Induced Microseismic Records

The mining-induced microseismic records were obtained from an accelerometer buried in the rock mass at the Huangtupo Copper and Zinc Mine. We could only collect acceleration measurement data from this mine. We employed a semi-synthetic method to construct a dataset containing acceleration, velocity, and displacement measurements. First, we reconstructed the microseismic records from the acceleration measurements using traditional methods. Then, we performed differential calculations on the displacement measurements to obtain the velocity and acceleration measurements. Finally, we added random noise to the acceleration measurements and randomly changed their signal-to-noise ratio (SNR). An example of the data-generating process using the semi-synthetic method is shown in Figure 5.

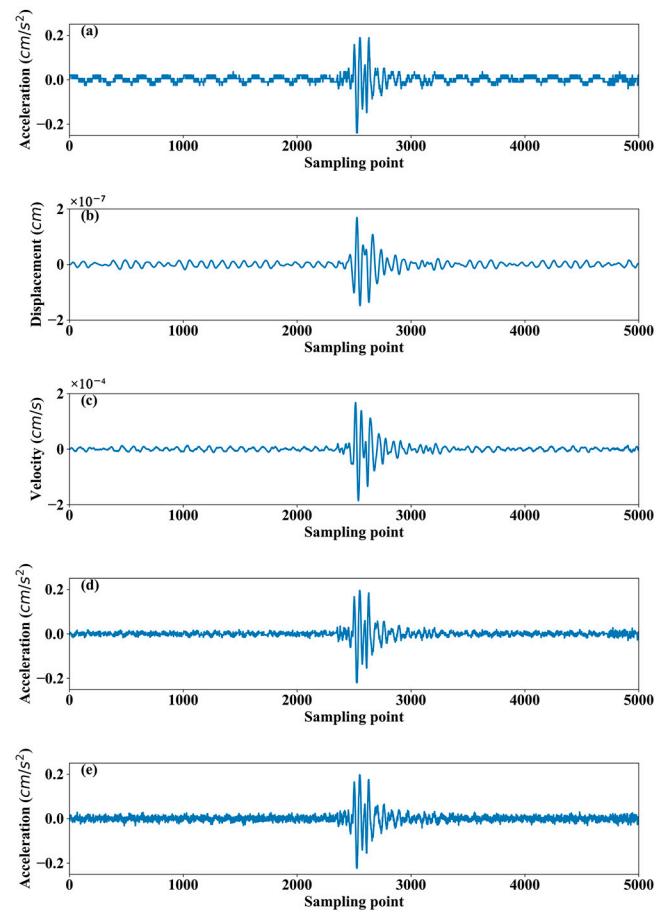


Figure 5. An example of the data-generating process using the semi-synthetic method. (a) The microseismic waveform of the acceleration measurement collected during the mining process. (b) The displacement measurement reconstructed from (a) by the traditional time-frequency reconstruction method. (c) The velocity measurement obtained by differential calculation of (b). (d) The acceleration measurement obtained by differential calculation of (c). (e) Random Gaussian white noise added to (d) to synthesize an acceleration measurement waveform with known displacement and velocity measurements.

We constructed a dataset containing 9500 sets of records for three types of measurements (displacement, velocity, and acceleration) using the aforementioned semi-synthetic method. Each microseismic record had a sampling frequency of 10 kHz and contained 2000 sampling points. This high sampling rate was based on the actual hardware setting of the mine's monitoring system, as mining-induced microseismic signals travel very short distances and contain abundant high-frequency components. From this dataset, 500 records were randomly chosen as the test set. It is important to note that the noise-addition step was used only for dataset generation. For both the microseismic and natural seismic datasets, we used identical training settings: a learning rate of 0.000001 (decaying after 100 epochs) and a total of 1000 epochs. No other parameter adjustments were introduced. The training loss, $L(G, F, D_x, D_y)$, as a function of the epoch number is shown in Figure 6.

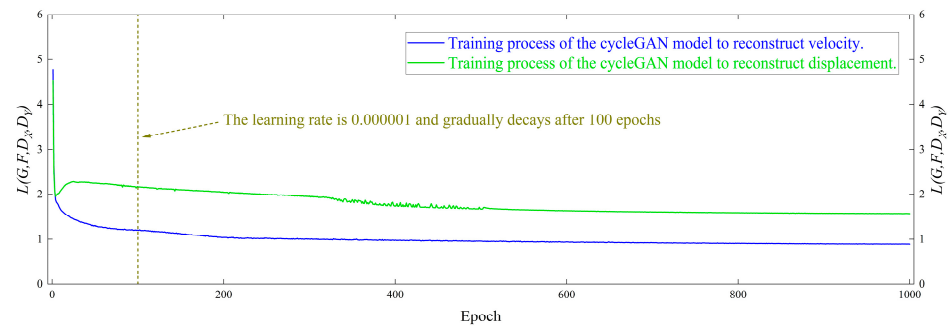


Figure 6. The training process of the two mapping functions, $F_{a2v}(x)$ and $F_{a2d}(x)$, based on CycleGAN.

After training of $F_{a2v}(x)$ and $F_{a2d}(x)$ was completed, a single microseismic record in the test set was randomly selected to test the effectiveness of our approach. As shown in Figure 7, the method proposed in this paper effectively reconstructed the velocity and displacement measurements from a microseismic acceleration waveform.

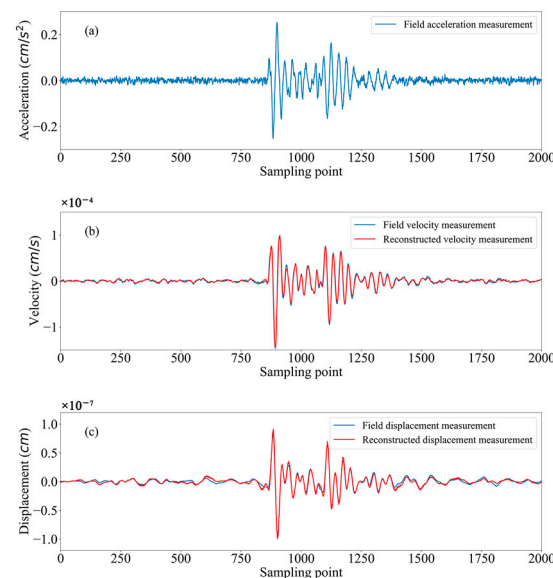


Figure 7. Microseismic record reconstruction results. (a) Microseismic acceleration measurement. (b) The blue line is the field velocity record corresponding to (a), and the red line is the velocity record reconstructed by CycleGAN. (c) The blue line is the field displacement record corresponding to (a), and the red line is the displacement record reconstructed by CycleGAN.

3.2. Experiment Based on Seismic Records

We designed an experiment based on field seismic records. These seismic records were obtained from the CESMD. The data from the data center include processed acceleration, velocity, and displacement measurements. Therefore, we selected 9500 sets of records collected between 2018 and 2021 for our experiment. Since these seismic records come from different stations, many of these records have different sampling rates. In order to maintain a consistent data benchmark for deep learning network training, we used interpolation to standardize the sampling rate of all records to 50 Hz, with a sampling window length of 20 s. We chose 50 Hz because it is a realistic and common standard for natural strong-motion networks. Unlike microseismic signals, natural seismic signals propagate over long distances, causing their high-frequency components to attenuate. Therefore, each seismic record contains 1000 sampling points. In addition, to make the

results verifiable, the seismic records were also processed using the semi-synthetic method.

Based on the configured training set and the CycleGAN-based reconstruction approach, we trained two CycleGAN models, $F_{a2v}(x)$ and $F_{a2d}(x)$, to reconstruct velocity and displacement measurements, respectively. The specific training process is shown in Figure 8.

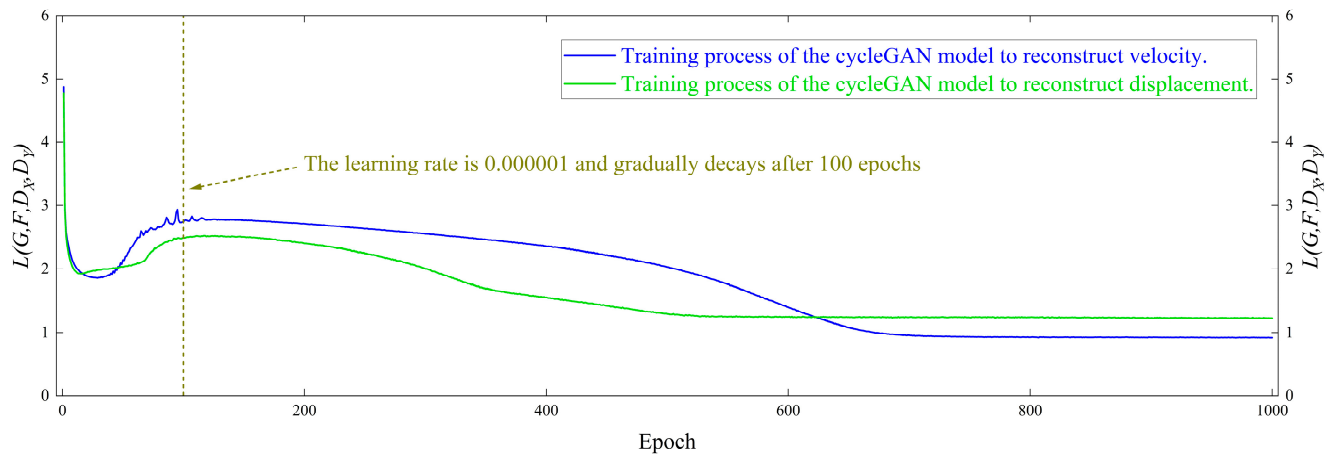


Figure 8. Training process of the two CycleGAN models, $F_{a2v}(x)$ and $F_{a2d}(x)$, for seismic record reconstruction.

After completing the training of the two CycleGAN models, $F_{a2v}(x)$ and $F_{a2d}(x)$, we randomly selected a natural seismic record from the test set to evaluate the method. As shown in Figure 9, our proposed method successfully reconstructed both the velocity and displacement measurements from a natural seismic acceleration waveform. Therefore, based on the preliminary verification using microseismic and seismic records, the method proposed in this article is feasible, and we further verify and analyze it in the following section.

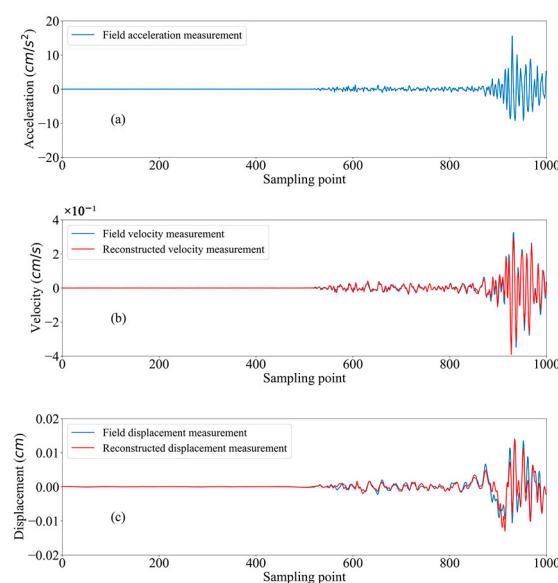


Figure 9. Seismic record reconstruction results. (a) Seismic acceleration measurement. (b) The blue line is the field velocity record corresponding to (a), and the red line is the velocity record reconstructed by CycleGAN. (c) The blue line is the field displacement record corresponding to (a), and the red line is the displacement record reconstructed by CycleGAN.

3.3. Comparison

After the above training process, we obtained four mapping functions. We applied the test set to these mapping functions and compared our approach with traditional methods. The traditional methods used for comparison were the reconstruction method combining frequency-domain integration with wavelet packet transform (FFT-WPT) and the reconstruction method combining frequency-domain integration with empirical mode decomposition (FFT-EMD). These two traditional methods integrate the signal in the frequency domain and then use wavelet packet decomposition or empirical mode decomposition to remove the trend term caused by noise. Although these two traditional methods are commonly used, they require manual parameter tuning for different datasets to achieve optimal results. The specific parameters we configured for FFT-WPT and FFT-EMD in our baseline experiments are detailed in Table 1. Because these parameters are sensitive to signal variations, applying them universally to large datasets is challenging. In contrast, our trained mapping functions process the data automatically without requiring manual parameter setup during inference.

Table 1. Parameter-setting requirements for various methods.

Method	Key Parameters Configured for Testing	Description/Purpose
Proposed approach (CycleGAN)	None (during inference)	Automatically reconstructs velocity/displacement end-to-end after training while remaining robust to input noise.
FFT-WPT	Wavelet basis: db4 Decomposition level: 3 Thresholding: Soft thresholding	Uses wavelet packet decomposition to filter out low-frequency trend terms after frequency-domain integration.
FFT-EMD	Decomposition mode: Standard EMD Trend removal: Removal of the last IMF	Integrates the signal in the frequency domain, then decomposes it into IMFs to subtract the baseline drift caused by noise.

Therefore, we fixed the parameters of the above two traditional methods through trial and comparison. Then, we used the above three methods to reconstruct the data in the test set in batches. In this way, the reliability of the various methods in simulated industrial application scenarios could be tested. Figure 10 shows the comparison results of some seismic records in the test set, and Figure 11 shows the comparison results of some microseismic records in the test set. The results show that the proposed parameter-free inference approach can reconstruct the velocity and displacement measurements effectively while remaining robust to noise in the input records.

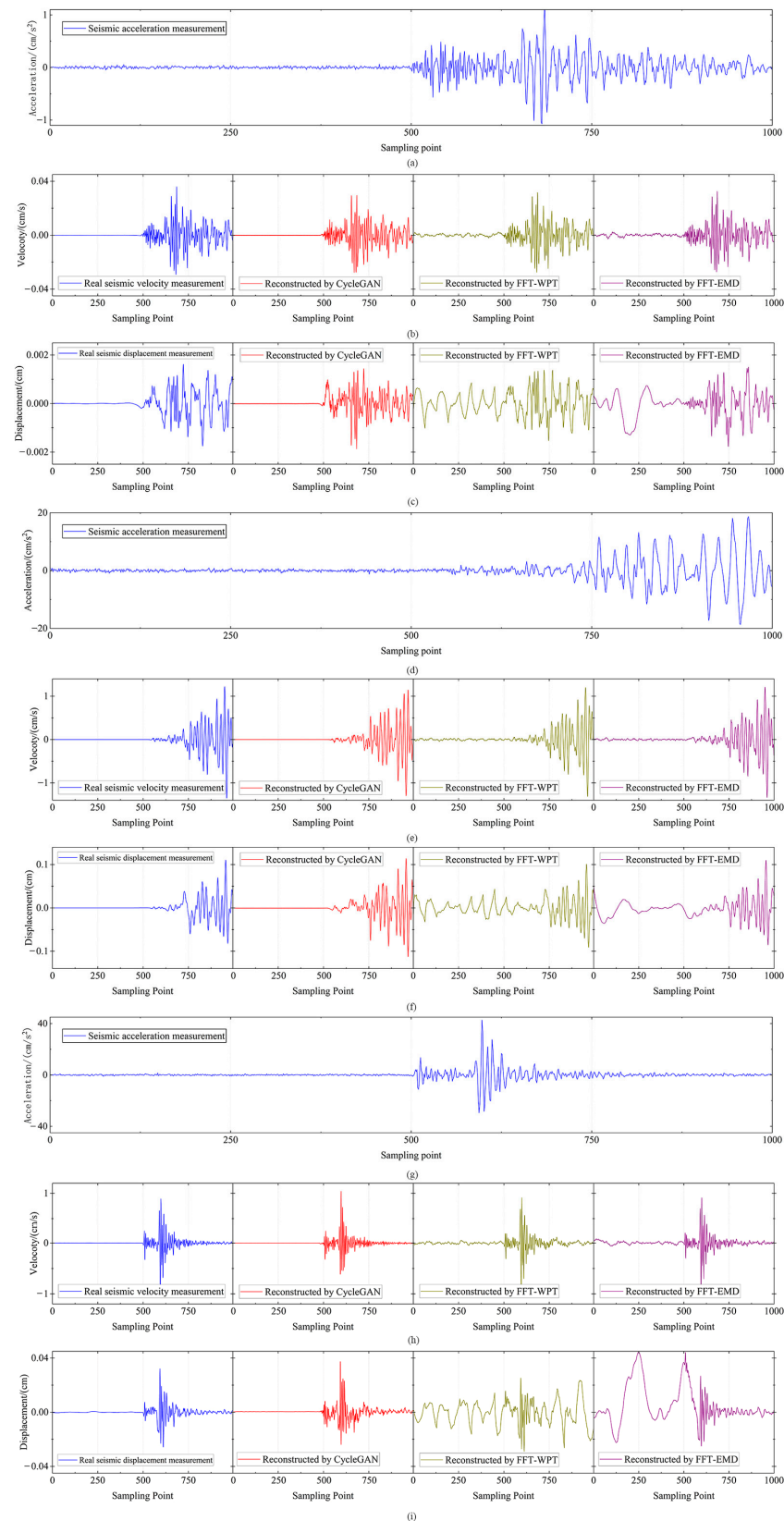


Figure 10. Comparison results of some seismic records in the test set. (a,d,g) Examples of seismic acceleration in the test set. (b,e,h) Comparison of real seismic velocity measurements, velocity measurements reconstructed by CycleGAN, velocity measurements reconstructed by FFT-WPT, and velocity measurements reconstructed by FFT-EMD. (c,f,i) Comparison of real seismic displacement measurements, displacement measurements reconstructed by CycleGAN, displacement measurements reconstructed by FFT-WPT, and displacement measurements reconstructed by FFT-EMD.

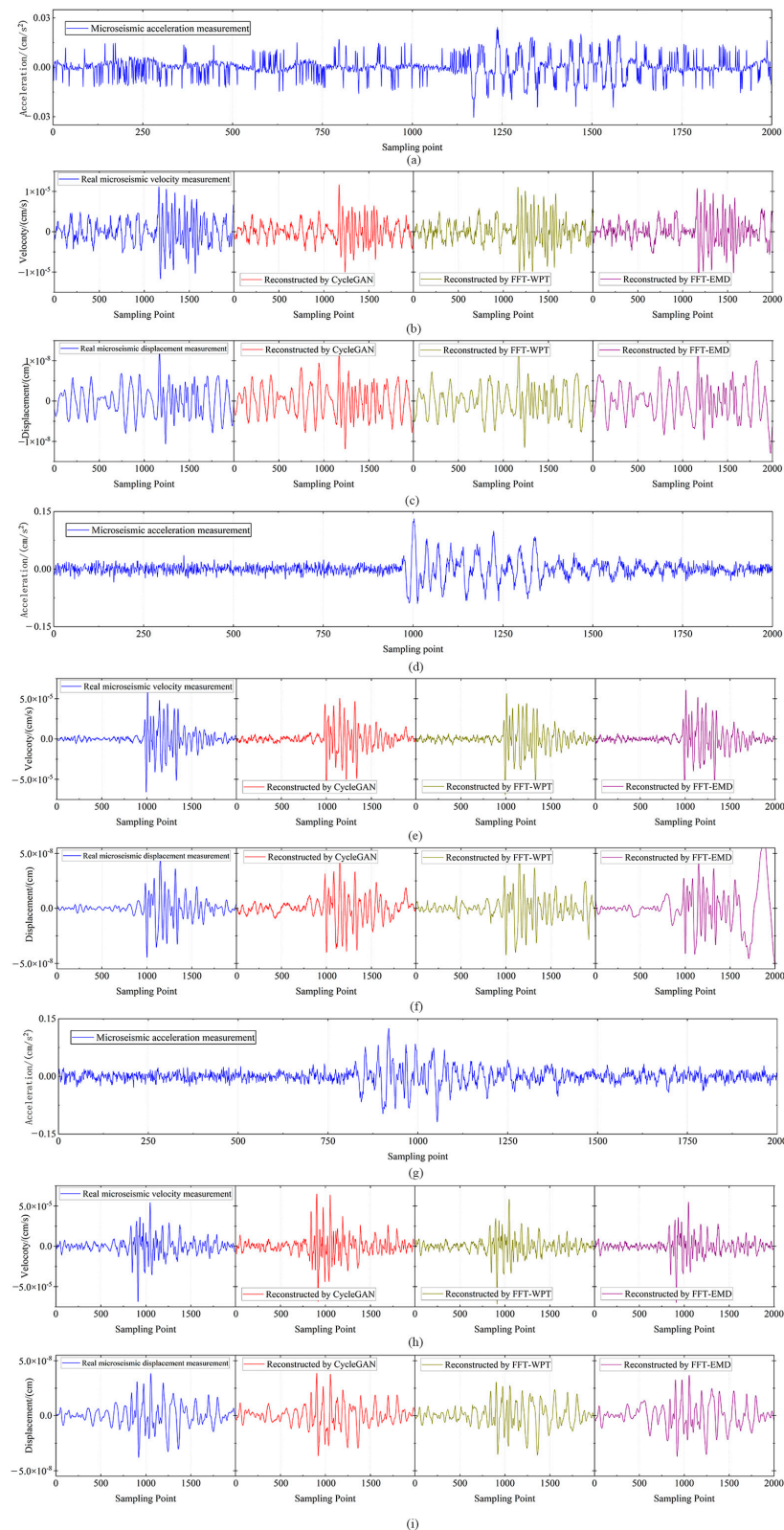


Figure 11. Comparison results of some microseismic records in the test set. **(a,d,g)** Examples of microseismic acceleration in the test set. **(b,e,h)** Comparison of real microseismic velocity measurements, velocity measurements reconstructed by CycleGAN, velocity measurements reconstructed by FFT-WPT, and velocity measurements reconstructed by FFT-EMD. **(c,f,i)** Comparison of real microseismic displacement measurements, displacement measurements reconstructed by CycleGAN, displacement measurements reconstructed by FFT-WPT, and displacement measurements reconstructed by FFT-EMD.

Further, we compared the three approaches across the entire test set. In order to quantitatively evaluate these methods, we referred to [13,16] and used three metrics, including the average peak error, average deviation error, and root-mean-square error, to evaluate the deviation of the reconstructed record from the reference velocity or displacement.

(1) The average peak error (Erp), which represents the average deviation at both positive and negative extremes of the time series, is defined as

$$Er_{peak}^{+} = \left| \frac{\max(X(t)) - \max(x(t))}{\max(x(t))} \right|, Er_{peak}^{-} = \left| \frac{\min(X(t)) - \min(x(t))}{\min(x(t))} \right|, \quad (12)$$

where $x(t)$ is the reference record and $X(t)$ is the reconstructed record.

$$Erp = \frac{1}{2}(Er_{peak}^{+} + Er_{peak}^{-}). \quad (13)$$

(2) The average deviation error (Err), denoting the average deviation of the peak value, is often an important and helpful metric for comparison.

$$Err = \frac{1}{2} \left(\left| \frac{\max(X(t) - x(t))}{\max(x(t))} \right| + \left| \frac{\min(X(t) - x(t))}{\min(x(t))} \right| \right). \quad (14)$$

(3) The root-mean-square error (Ers) represents the overall deviation of the whole time series at every instant:

$$Ers = \sqrt{\frac{\sum_{i=0}^{N-1} (x(t_i) - X(t_i))^2}{N}}, \quad (15)$$

where N is the number of sampling points. Using these metrics, we further compared and analyzed the performance of the three methods.

For the seismic records in the test set, the above evaluation metrics were calculated for the velocity and displacement records reconstructed by the various methods, and the results are shown in Figure 12 and Table 2.

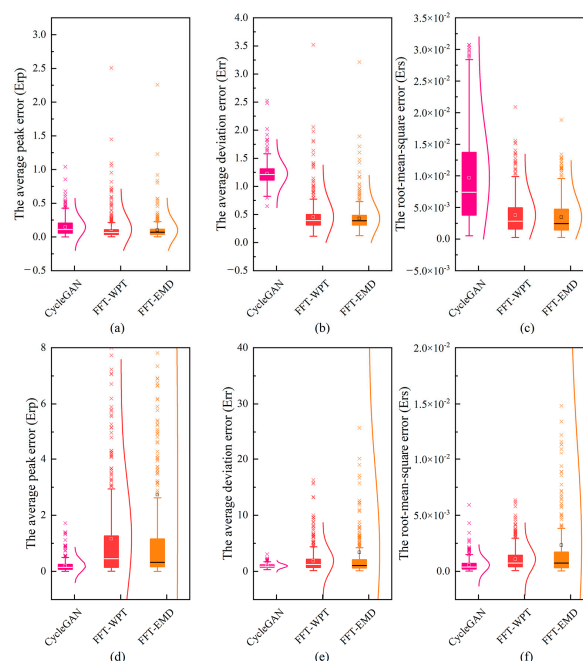


Figure 12. The calculation results for the three metrics in the different reconstruction processes are represented by box plots and distribution curves. (a) Average peak error (Erp) of seismic velocity

measurement reconstruction by different methods. (b) Average deviation error (*Err*) of seismic velocity measurement reconstruction by different methods. (c) Root-mean-square error (*Ers*) of seismic velocity measurement reconstruction by different methods. (d) Average peak error (*Erp*) of seismic displacement measurement reconstruction by different methods. (e) Average deviation error (*Err*) of seismic displacement measurement reconstruction by different methods. (f) Root-mean-square error (*Ers*) of seismic displacement measurement reconstruction by different methods.

Table 2. Statistical values of the evaluation metrics for seismic record reconstruction.

Measure- ment	Method	Average Peak Error (<i>Erp</i>)				Average Deviation Error (<i>Err</i>)				Root-Mean-Square Error (<i>Ers</i>)			
		μ	σ^2	Max	Min	μ	σ^2	Max	Min	μ	σ^2	Max	Min
Velocity reconstruc- tion	CycleGAN	0.1478	0.0169	1.0407	0.0011	1.2269	0.0346	2.5250	0.6487	0.0097	7.6×10^{-6}	0.0308	5.2×10^{-4}
	FFT-WPT	0.1129	0.0336	2.5065	0.0031	0.4553	0.0807	3.5183	0.1126	0.0038	8.8×10^{-6}	0.0209	2.6×10^{-4}
	FFT-EMD	0.0992	0.0214	2.2573	0.0022	0.4282	0.0556	3.2142	0.1228	0.0035	5.6×10^{-5}	0.0188	2.5×10^{-4}
Displace- ment re- construc- tion	CycleGAN	0.2004	0.0439	1.7201	1.3×10^{-4}	0.9783	0.1148	3.0627	0.3063	5.6×10^{-4}	3.3×10^{-7}	0.0059	2.8×10^{-5}
	FFT-WPT	1.1658	3.9069	15.550	0.0054	1.8792	4.4448	16.2865	0.1502	0.0011	1.0×10^{-6}	0.0064	7.2×10^{-5}
	FFT-EMD	2.7329	200.51	248.72	0.0038	3.4068	202.15	249.7090	0.1258	0.0023	8.0×10^{-5}	0.1260	3.9×10^{-5}

For the reconstruction of seismic velocity measurements, the mean *Erp*, *Err*, and *Ers* values on the test set for our approach were 0.1478, 1.2269, and 0.0097, respectively. The variances of *Erp*, *Err*, and *Ers* were 0.0169, 0.0346, and 7.6×10^{-6} , and the maximum *Erp*, *Err*, and *Ers* values were 1.0407, 2.5250, and 0.0308, respectively. In contrast, the mean *Erp*, *Err*, and *Ers* values on the test set for FFT-WPT were 0.1129, 0.4553, and 0.0038, respectively. The variances of *Erp*, *Err*, and *Ers* were 0.0336, 0.0807, and 8.8×10^{-6} , and the maximum *Erp*, *Err*, and *Ers* values were 2.5065, 3.5183, and 0.0209, respectively. The mean *Erp*, *Err*, and *Ers* values on the test set for FFT-EMD were 0.0992, 0.4282, and 0.0035, respectively. The variances of *Erp*, *Err*, and *Ers* were 0.0214, 0.0556, and 5.6×10^{-5} , and the maximum *Erp*, *Err*, and *Ers* values were 2.2573, 3.2142, and 0.0188, respectively. It can be seen from the velocity reconstruction results that the traditional methods yielded lower error metrics than our deep learning method: the mean *Ers* of CycleGAN was 0.0097, whereas those of FFT-WPT and FFT-EMD were 0.0038 and 0.0035, respectively. The mean *Ers* of our method was about 2.6 and 2.8 times those of FFT-WPT and FFT-EMD, respectively. This difference is acceptable in the present setting because the noise interference in the velocity reconstruction is comparatively mild, and the traditional methods can be tuned effectively; in practical deployment, however, our parameter-free inference approach avoids the per-dataset tuning that the traditional methods require.

Moreover, for the reconstruction of seismic displacement measurements, the mean *Erp*, *Err*, and *Ers* values on the test set for the method proposed in this paper were 0.2004, 0.9783, and 5.6×10^{-4} , respectively. The variances of *Erp*, *Err*, and *Ers* were 0.0439, 0.1148, and 3.3×10^{-7} , and the maximum *Erp*, *Err*, and *Ers* values were 1.7201, 3.0627, and 0.0059, respectively. In contrast, the mean *Erp*, *Err*, and *Ers* values on the test set for FFT-WPT were 1.1658, 1.8792, and 0.0011, respectively. The variances of *Erp*, *Err*, and *Ers* were 3.9069, 4.4448, and 1.0×10^{-6} , and the maximum *Erp*, *Err*, and *Ers* values were 15.550, 16.2865, and 0.0064, respectively. The mean *Erp*, *Err*, and *Ers* values on the test set for FFT-EMD were 2.7329, 3.4068, and 0.0023, respectively. The variances of *Erp*, *Err*, and *Ers* were

200.51, 202.15, and 8.0×10^{-5} , and the maximum *Erp*, *Err*, and *Ers* values were 248.72, 249.70, and 0.1260, respectively. These results clearly show that our approach outperformed the traditional methods by a large margin. The very large variance and extreme maximum values reported for FFT-EMD (for example, *Erp*: variance, 200.51; maximum value, 248.72) indicate that a small number of test records produced extreme errors under the fixed EMD parameters, so that the mean values of the traditional methods are sensitive to such outliers, whereas the CycleGAN errors remained stable over the whole test set. Considering Figures 10 and 12, it is challenging to apply fixed parameters in traditional methods to all data, and parameter adjustments must be made. At the same time, when reconstructing displacement, the interference of noise is significantly increased, which affects the reconstruction performance of these methods. However, the method proposed in this paper not only does not need any parameters to be set but also remains robust to noise during the reconstruction process, thereby successfully reconstructing high-quality velocity and displacement measurements.

To better illustrate the precision of each approach, we directly compared their average errors based on Table 2. For seismic displacement reconstruction, the mean root-mean-square error (*Ers*) for CycleGAN was 5.6×10^{-4} . This error was about 50% lower than that of FFT-WPT (1.1×10^{-3}) and about 76% lower than that of FFT-EMD (2.3×10^{-3}). This shows that CycleGAN clearly achieved higher accuracy in recovering displacement.

For seismic velocity reconstruction, the mean *Ers* values for CycleGAN, FFT-WPT, and FFT-EMD were 0.0097, 0.0038, and 0.0035, respectively. Although they were of the same order of magnitude, CycleGAN reached this precision automatically, without the manual parameter adjustment required by FFT-WPT and FFT-EMD.

Additionally, for the test set of microseismic records, the above evaluation metrics were calculated for the velocity and displacement records reconstructed by the various methods, and the results are shown in Figure 13 and Table 3. The microseismic results exhibited the same overall pattern as the seismic results. For displacement reconstruction, CycleGAN achieved the lowest errors (mean *Erp*, *Err*, and *Ers* values of 0.0435, 0.2584, and 3.4×10^{-9} , compared with 0.0689, 0.3108, and 3.7×10^{-9} for FFT-WPT and 0.1467, 0.3950, and 7.2×10^{-9} for FFT-EMD). For velocity reconstruction, the traditional methods yielded slightly lower mean *Erp* and *Err* than CycleGAN, while the mean *Ers* values of the three methods were comparable (3.4×10^{-6} for CycleGAN, 3.1×10^{-6} for FFT-WPT, and 3.0×10^{-6} for FFT-EMD).

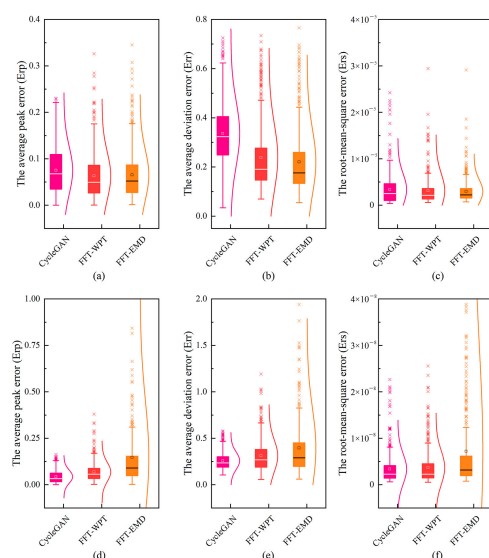


Figure 13. The calculation results for the three metrics in the different reconstruction processes are represented by box plots and distribution curves. (a) Average peak error (*Erp*) of microseismic

velocity measurement reconstruction by different methods. (b) Average deviation error (*Err*) of microseismic velocity measurement reconstruction by different methods. (c) Root-mean-square error (*Ers*) of microseismic velocity measurement reconstruction by different methods. (d) Average peak error (*Erp*) of microseismic displacement measurement reconstruction by different methods. (e) Average deviation error (*Err*) of microseismic displacement measurement reconstruction by different methods. (f) Root-mean-square error (*Ers*) of microseismic displacement measurement reconstruction by different methods.

Table 3. Statistical values of the evaluation metrics for microseismic record reconstruction.

Measure- ment	Method	Average Peak Error (<i>Erp</i>)				Average Deviation Error (<i>Err</i>)				Root-Mean-Square Error (<i>Ers</i>)			
		μ	σ^2	Max	Min	μ	σ^2	Max	Min	μ	σ^2	Max	Min
Velocity reconstruc- tion	CycleGAN	0.0752	0.0026	0.2302	0.0002	0.3362	0.0171	0.7249	0.0342	3.4×10^{-6}	1×10^{-11}	2.4×10^{-5}	3.6×10^{-7}
	FFT-WPT	0.0633	0.0026	0.3261	0.0004	0.2388	0.0186	0.7340	0.0697	3.1×10^{-6}	1×10^{-11}	4.1×10^{-5}	6.1×10^{-7}
	FFT-EMD	0.0654	0.0028	0.3454	0.0014	0.2209	0.0178	0.7658	0.0547	3.0×10^{-6}	6×10^{-12}	2.9×10^{-5}	7.3×10^{-7}
Displace- ment re- construc- tion	CycleGAN	0.0435	0.0012	0.1625	2.0×10^{-5}	0.2584	0.0088	0.5784	0.1051	3.4×10^{-9}	1×10^{-17}	2.3×10^{-8}	6×10^{-10}
	FFT-WPT	0.0689	0.0026	0.3796	0.0020	0.3108	0.0288	1.1914	0.0568	3.7×10^{-9}	1×10^{-17}	2.6×10^{-8}	5×10^{-10}
	FFT-EMD	0.1467	0.0924	5.1594	0.0020	0.3950	0.1834	6.1529	0.0609	7.2×10^{-9}	5×10^{-16}	4.5×10^{-7}	7×10^{-10}

4. Discussion

Before discussing the detailed performance, we must acknowledge a limitation regarding the microseismic dataset. In the monitored underground mine, only accelerometers were deployed. There were no collocated velocity or displacement sensors to provide independent “ground-truth” measurements. Consequently, the microseismic velocity and displacement labels used for training were generated using traditional mathematical methods. We recognize that evaluating the model solely on this semi-synthetic dataset presents a circular validation issue, as the network essentially learns to approximate the traditional method rather than absolute physical measurements.

However, using these proxy labels allowed the CycleGAN model to establish a basic mapping relationship. The core contribution of our deep learning approach lies in its behavior under noisy conditions. When random noise is introduced into acceleration data, traditional methods require manual parameter adjustments and often fail to integrate accurately. In contrast, the trained CycleGAN model can bypass manual tuning and effectively separate the signal from noise. Additionally, to ensure our method is not limited to mimicking traditional outputs, we validated the approach on the CESMD natural seismic dataset, which provides independently processed records as a more reliable baseline.

The above experimental results show that the main factor that affects the reconstruction performance of different methods is the noise in the signal, especially in displacement reconstruction. The experimental results also show that our approach can effectively reduce the error caused by noise in the reconstruction process. Therefore, this section analyzes and discusses the influence of the SNR on reconstruction performance and robustness to noise during the displacement reconstruction process based on the seismic test set. In this paper, SNR is defined as the logarithmic ratio of noisy signal energy to noise energy:

$$SNR = 10 \times \lg\left(\frac{E}{E_{noise}}\right), \quad (16)$$

where E is the energy of a noisy signal and E_{noise} is the energy of the noise. According to Formula (16), we calculated the SNR of all records in the seismic test set (SNR0), the SNR of the displacement records reconstructed by CycleGAN (SNR1), the SNR of the displacement records reconstructed by FFT-WPT (SNR2), and the SNR of the displacement records reconstructed by FFT-EMD (SNR3). The SNR calculation results are shown in Figure 14 and Table 4. The percentages of records with an SNR greater than 10 for SNR0, SNR1, SNR2, and SNR3 were 37.6%, 31.6%, 11.6%, and 20.6%, respectively. It can be seen that the SNR distribution of the displacement record dataset reconstructed by CycleGAN was the closest to that of the input dataset.

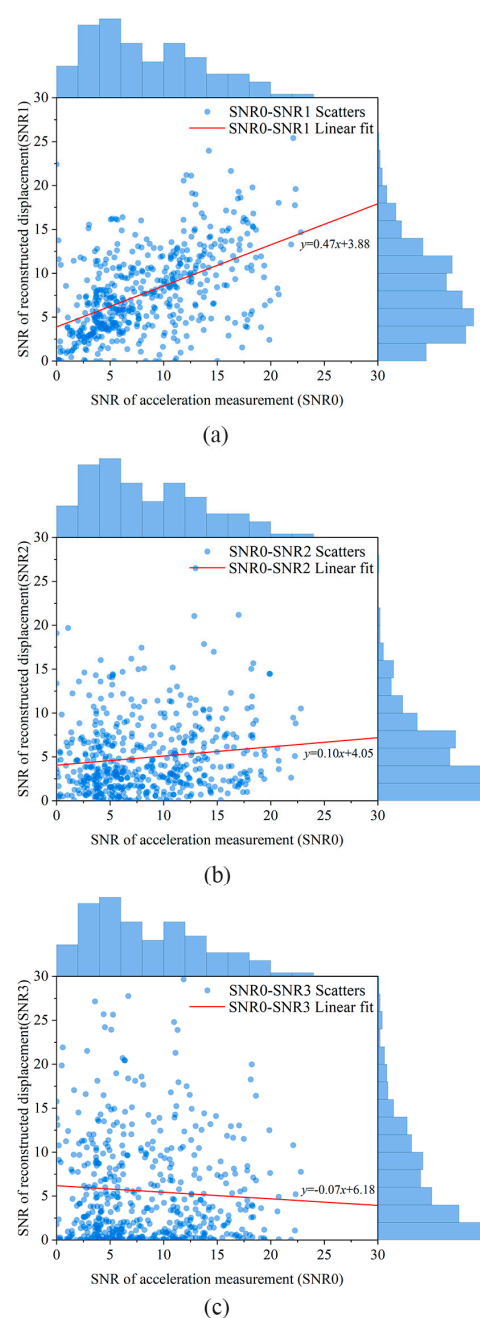


Figure 14. SNR calculation results for the different datasets. SNR0 is the SNR of all records in the seismic test set. SNR1 is the SNR of the displacement records reconstructed by CycleGAN. SNR2 is

the SNR of the displacement records reconstructed by FFT-WPT. SNR3 is the SNR of the displacement records reconstructed by FFT-EMD. (a) Correspondence between SNR0 and SNR1. (b) Correspondence between SNR0 and SNR2. (c) Correspondence between SNR0 and SNR3.

Table 4. SNR calculation results for the different datasets.

Name	Description	$\text{SNR} \leq 5$	$5 < \text{SNR} \leq 10$	$10 < \text{SNR} \leq 15$	$15 < \text{SNR} \leq 20$	$20 < \text{SNR}$
SNR0	SNR of all records in the seismic test set.	164	148	123	57	8
SNR1	SNR of the displacement records reconstructed by CycleGAN.	165	177	118	33	7
SNR2	SNR of the displacement records reconstructed by FFT-WPT	305	137	44	11	3
SNR3	SNR of the displacement records reconstructed by FFT-EMD	297	100	66	21	16

Moreover, as shown in Figure 14 and Table 4, we compared the robustness of the different methods to noisy input by analyzing the distribution of the reconstructed SNRs. Since the amplitude and energy of the reconstructed displacement differed from those of the input acceleration, a universal improvement in the SNRs after processing was neither expected nor claimed; the comparison therefore indicates how close the distributions of the reconstructed SNRs remained to those of the input records. According to Table 4, the displacement records reconstructed by CycleGAN showed the smallest degradation: 31.6% of them retained an SNR greater than 10, compared with 37.6% for the input acceleration records, whereas the corresponding fractions for the records reconstructed by FFT-WPT and FFT-EMD dropped to 11.6% and 20.6%, respectively. The scatter plots in Figure 14 also show that when the input acceleration data had a low SNR, the displacement reconstructed by CycleGAN tended to maintain a more stable signal quality. These results indicate that, under noisy conditions, our method handles data more stably than the tested traditional approaches, which require careful manual parameter tuning to avoid strong degradation.

Additionally, we tested the reliability of the deep learning method by adding noise of different intensities to the seismic records of the test set. We again carried out the displacement measurement reconstruction experiment under four different SNRs (20, 15, 10, 5). As shown in Figure 15, the acceleration measurements of the seismic records were assigned different SNRs and were reconstructed using the deep learning method and traditional methods. The results show that when the signal-to-noise ratio gradually decreased, both methods were affected to a certain extent. However, thanks to the addition of noise to the training data, the deep learning method effectively reduced the interference caused by noise during reconstruction. Even if a batch of noisy datasets is processed, better results can be obtained. The parameters of traditional methods have to be carefully adjusted to adapt to different SNRs.

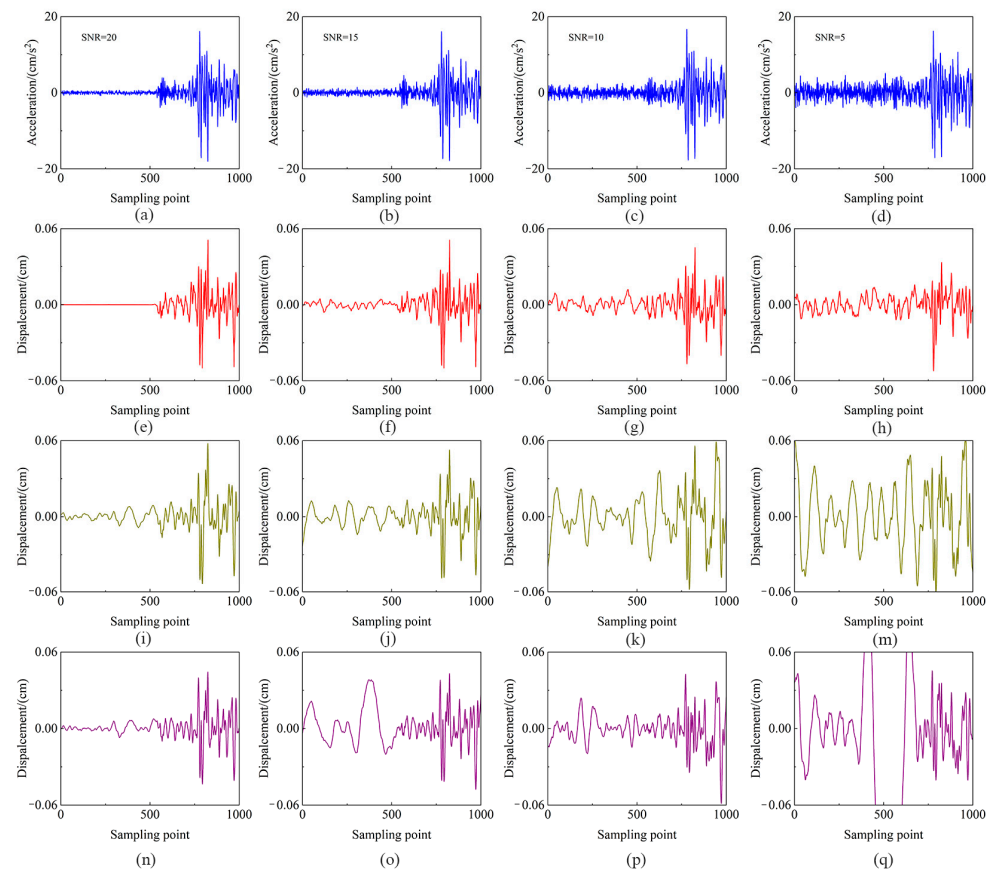


Figure 15. The influence of SNR on the performance of reconstruction methods. **(a–d)** Acceleration measurements under different SNRs. **(e–h)** Reconstructed displacement measurements under different SNRs by CycleGAN. **(i–m)** Reconstructed displacement measurements under different SNRs by FFT-WPT. **(n–q)** Reconstructed displacement measurements under different SNRs by FFT-EMD.

Finally, to test how the method performs in a real-world scenario, we applied it to a recent earthquake. As shown in Figure 16, on October 13, 2021, a 5.4 MWW earthquake occurred in El Calafate, Santa Cruz, Argentina. This seismic event was neither in the training set nor in the test set and occurred later than any seismic event in the dataset we used. We obtained seismic records of the El Calafate earthquake collected by seismic stations (Cerro Castillo, Chile, and Puerto Natales). Each seismic station provided the raw three-component seismic record and the data after USGS automated strong-motion processing. These processed data contained the preliminary reconstructed velocity and displacement records and are subject to revision. Based on these data, we processed the raw seismic records using our approach and evaluated its practical potential. It should be noted that data from USGS automated processing were used here as an established reference baseline for comparison, rather than an independent ground truth. Furthermore, testing on a single event from two stations is a preliminary demonstration, and more comprehensive field testing will be conducted in future work.

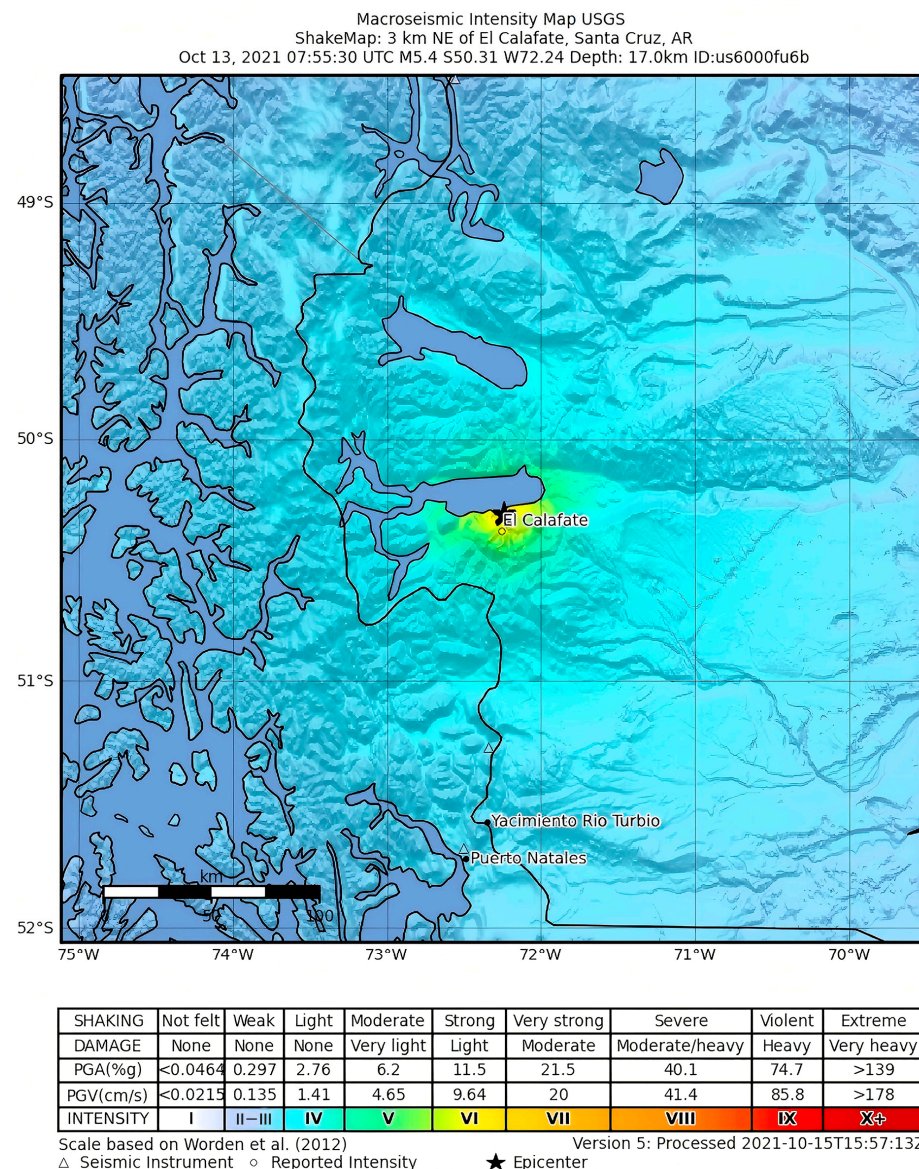


Figure 16. On October 13, 2021, a 5.4 MWW earthquake occurred in El Calafate, Santa Cruz, Argentina. The ShakeMap was obtained from [39].

In Figure 17(a), Figure 17(b), and Figure 17(c), the raw seismic records from the seismic station in Cerro Castillo, Chile, are shown. The blue lines in Figure 17(d), Figure 17(e), and Figure 17(f) are the velocity records of the different channels reconstructed by USGS automated processing, respectively. The red lines in Figure 17(d), Figure 17(e), and Figure 17(f) are the velocity records of the different channels reconstructed by our approach, respectively. The blue lines in Figure 17(g), Figure 17(h) and Figure 17(i) are the displacement records of the different channels reconstructed by USGS automated processing, respectively. The red lines in Figure 17(g), Figure 17(h), and Figure 17(i) are the displacement records of the different channels reconstructed by our approach, respectively. Specifically, we also used the average peak error, average deviation error, and root-mean-square error to evaluate the differences between the reconstruction results. The results are shown in Table 5. Similarly, the processing and comparison results of the seismic records in Puerto Natales are shown in Figure 18 and Table 5.

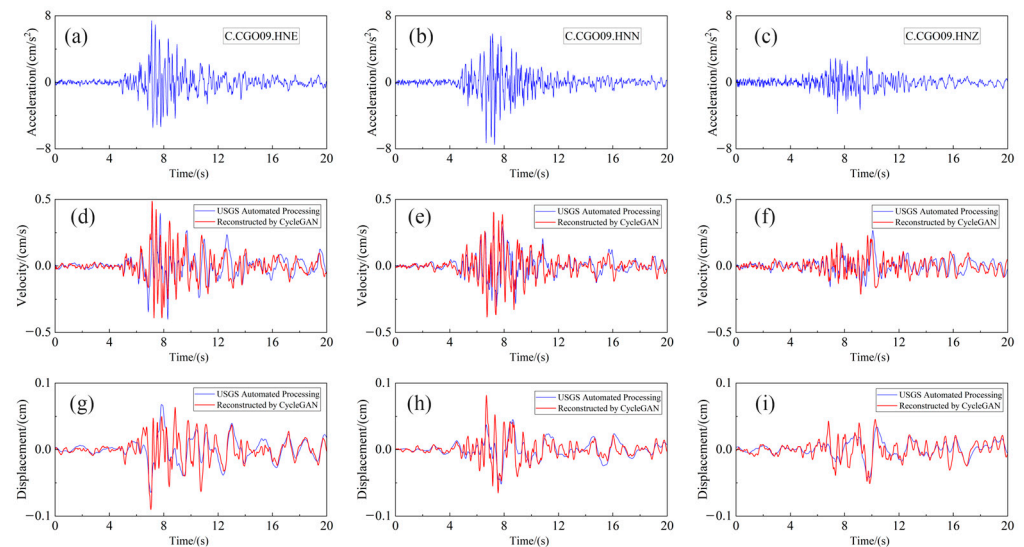


Figure 17. Comparison of the reconstruction results for the station records from Cerro Castillo, Chile, between USGS automated processing and our approach. (a–c) Raw seismic records. (d–f) Velocity records of the corresponding channels reconstructed by the USGS automated processing (blue lines) and the proposed approach (red lines). (g–i) Displacement records of the corresponding channels reconstructed by the USGS automated processing (blue lines) and the proposed approach (red lines).

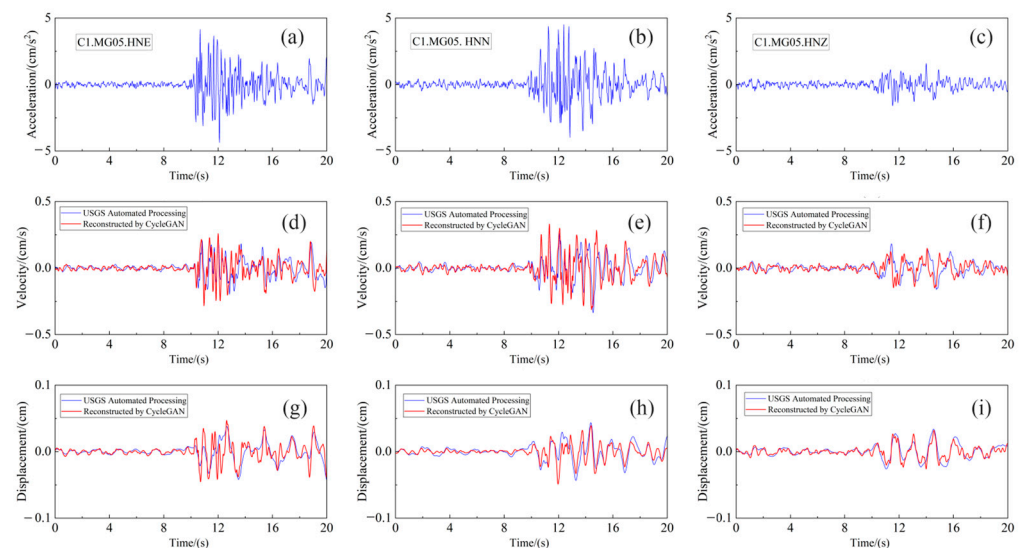


Figure 18. Comparison of the reconstruction results for the station records from Puerto Natales between USGS automated processing and our approach. (a–c) Raw seismic records. (d–f) Velocity records of the corresponding channels reconstructed by the USGS automated processing (blue lines) and CycleGAN (red lines). (g–i) Displacement records of the corresponding channels reconstructed by the USGS automated processing (blue lines) and CycleGAN (red lines).

Table 5. Average peak error, average deviation error, and root-mean-square error between the reconstruction results.

Station	Reconstruction	Channel	Figure	<i>E_{rp}</i>	<i>E_{rr}</i>	<i>E_{rs}</i>
Cerro Castillo, Chile	Velocity	HNE	Figure 17a2	0.1012	0.9256	0.0856
		HNN	Figure 17b2	0.2891	0.9719	0.0686
		HNZ	Figure 17c2	0.1047	1.0198	0.0546
	Displacement	HNE	Figure 17a3	0.2297	0.9433	0.0158

Puerto Natales		HNN	Figure 17b3	0.5290	0.9506	0.0115
		HNZ	Figure 17c3	0.2656	0.9887	0.0098
	Velocity	HNE	Figure 18a2	0.3160	1.0947	0.0579
		HNN	Figure 18b2	0.0969	1.0360	0.0736
		HNZ	Figure 18c2	0.1300	1.0523	0.0482
	Displacement	HNE	Figure 18a3	0.1562	1.0475	0.0103
		HNN	Figure 18b3	0.1167	0.6902	0.0089
		HNZ	Figure 18c3	0.0292	0.5834	0.0053

As shown in Table 5, the mean average peak error, average deviation error, and root-mean-square error for velocity reconstruction were 0.1730, 1.0167, and 0.0648, respectively. The mean average peak error, average deviation error, and root-mean-square error for displacement reconstruction were 0.2211, 0.8673, and 0.0103, respectively. Moreover, through visual observation and comparison of Figure 17 and Figure 18, it is easy to see the similarities and differences between the reconstructions. The comparison between the two processing methods shows that the overall reconstructed velocity and displacement records are very similar, and the main difference lies in the details. The results show that our approach can achieve basic reconstruction and retain more details.

Furthermore, we must note a limitation regarding the physical consistency of the current approach. In this study, velocity and displacement are reconstructed by two separate mapping functions (F_{a2v} and F_{a2d}) trained independently. We did not explicitly enforce the mathematical integration or differentiation relationships (i.e., ensuring that the derivative of the reconstructed displacement exactly matches the reconstructed velocity) within the network's loss functions. Although post-processing checks show that the network outputs generally follow this physical rule—since the training labels themselves were generated through integration—a strict mathematical constraint is missing. Incorporating physical kinematic constraints (such as physics-informed loss functions) into the adversarial training process will be a key focus of our future work to ensure strict integration and differentiation consistency.

5. Conclusions

In this study, we proposed an automated data-driven approach for the reconstruction of velocity and displacement from seismic acceleration measurements via CycleGAN. We designed the network structure and parameters of CycleGAN to construct two mapping functions, $F_{a2v}(x)$ and $F_{a2d}(x)$, from the acceleration dataset to the velocity and displacement datasets, which remained robust to noise, thereby enhancing reconstruction accuracy. Furthermore, once we have constructed these mapping functions, we can use them without setting or adjusting any parameters.

Two datasets containing microseismic and seismic records, one from the Huangtupo Copper and Zinc Mine in China and the other from the Center for Engineering Strong Motion Data, were constructed using a semi-synthetic method. Based on these data, we tested our approach and compared it with two commonly used traditional methods. Furthermore, three metrics, the average peak error (Erp), average deviation error (Err), and root-mean-square error (Ers), were used to evaluate reconstruction performance. For the reconstruction of seismic velocity measurements, the mean Erp , Err , and Ers values on the test set for the approach proposed in this paper were 0.1478, 1.2269, and 0.0097, respectively. Moreover, for the reconstruction of seismic displacement measurements, the mean Erp , Err , and Ers values on the test set for the method proposed in this paper were 0.2004, 0.9783, and 5.6×10^{-4} , respectively. Through a comparison of these metrics, CycleGAN significantly outperformed the traditional methods in displacement reconstruction while

showing slightly higher errors in velocity reconstruction. Overall, the main advantage of CycleGAN is its ability to process data automatically and remain robust to input noise without manual parameter tuning.

In summary, the clear advantages of the proposed method are its non-parametric nature and its robustness against noise. Unlike traditional methods that require experienced personnel to adjust parameters for different datasets, our trained CycleGAN models can be applied directly. This method shows strong potential for automated real-time monitoring in practical applications. It can be integrated into the processing software of mining microseismic systems or natural seismic stations. This will allow for automatic and rapid conversion of massive amounts of acceleration data into velocity and displacement records, which is highly beneficial for fast source parameter calculation and early hazard evaluation.

Additionally, through statistical analysis of the SNRs of each dataset before and after reconstruction, we found that our approach remained robust to noise during the reconstruction process. We designed and implemented comparative experiments on reconstruction performance under different SNRs to verify this finding. Also, we compared the existing processed records to verify the generalization of our method. In summary, the method proposed in this paper reconstructs seismic velocity or displacement records without setting parameters, remains robust to input noise to achieve better reconstruction, and demonstrates good prospects for practical application.

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