ENHANCING SEISMIC NOISE SUPPRESSION USING THE NOISE2NOISE FRAMEWORK

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ABSTRACT

Although supervised deep learning (DL) offers a potent solution for removing noise from seismic records, challenges are encountered owing to the scarcity of noise-free labels. The innovative Noise2Noise method eliminates the need for clean training targets and extends the applicability of deep learning to seismic data denoising. In this study, we introduce the Noise2Noise Enhancement (N2NE) framework, which improves upon the conventional noise reduction methods used in seismic processing. The applicability of this framework was quantitatively examined using actual field noise under two scenarios: with and without repeated shots. In scenarios with repeated shots, the N2NE framework enhances the conventional stacking method. In addition, the substack strategy, which employs smaller substacks for preliminary noise suppression before DL training, boosts noise suppression. In scenarios without repeated shots, the N2NE framework refines conventional denoising methods (F-X deconvolution) by utilizing information from the common-shot and receiver domains. The N2NE framework lays a foundation for future research on N2N-based seismic denoising methods and contributes to improving the quality of seismic records and the efficiency of data acquisition.

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INTRODUCTION

Denoising is a crucial step in seismic processing, particularly when seismic records are contaminated with random and coherent noise. Such noise obscures useful signals (reflections) and significantly reduces the signal-to-noise ratio (S/N). This degradation in signal fidelity can result in the misinterpretation of subsurface structures and unreliable results in the inversion process. To address the challenge of using low-S/N data, various methods have been proposed over the past several decades to attenuate unwanted noise.

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Prediction filter-based methods, including F-X deconvolution (Canales, 1984; Gulunay, 1986) and polynomial filters (Lu and Liu, 2006; Liu et al., 2011), separate the signal from noise by utilizing the predictable nature of the seismic signal and the unpredictable nature of noise. For example, F-X deconvolution exploits the property that a linear or quasi-linear seismic signal in the t-x domain is equivalent to the predictable superposition of harmonics in the f-x domain. The median filter (Bednar, 1983) is a widely accepted statistical noise suppression method that attenuates random noise by selecting a median value within a moving window across the noisy data. Sparse transformation-based algorithms can convert noisy data into a sparse domain to selectively attenuate noise using a thresholding coefficient. To achieve this objective, methods including wavelet (Mousavi et al., 2016), curvelet (Neelamani et al., 2008), seislet (Fomel and

Liu, 2010), and radon (Gholami, 2017) transformations with fixed basis functions have proven effective. Similarly, decomposition methods, such as singular value decomposition (Bekara and van der Baan, 2007), empirical mode decomposition (Bekara and van der Baan, 2009), and ensemble empirical mode decomposition (Wang et al., 2012) separate noisy data into modes with different frequency bands. The dictionary-learning-based denoising method (Zhu et al., 2015) represents seismic data using a set of adaptive basis functions from a learned dictionary. A dictionary is typically represented as an explicit matrix involving an iterative training process.

Vertical stacking is the most widely used and reliable denoising technique used for seismic processing. The radiant energy of vibroseis is restricted by both equipment limitations and the surrounding environment (road conditions and acceptable noise level). Repeated shots at the same point are combined to obtain sufficient source energy. The tradeoff between the quality of the record and the cost of the survey determines the number of folds. Under specific ideal conditions where the signal is consistent and the noise is stationary and random, conventional straight stacking, which calculates the arithmetic mean of the signals, ensures complete noise reduction. However, these ideal conditions are often not met; consequently, the effectiveness of noise reduction through straight stacking is limited. Therefore, diversity stacking, in which each

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trace is multiplied and weighted by a scale factor before stacking, is utilized in more complicated record models.

Recent advances in hardware technology have enabled the extensive use of deep learning methodologies in a wide range of seismic data processing tasks such as velocity inversion (Yang and Ma, 2019), first-arrival picking (Hu et al., 2019), fault detection (Xiong et al., 2018), deblending (Luiken et al., 2024), and reconstruction (Liu et al., 2021). Deep learning has also been applied effectively to suppress seismic noise. Deep neural networks (DNNs), particularly those that use supervised learning algorithms, have demonstrated significant effectiveness. Numerous studies have used extensively labeled datasets for DNN training. These datasets, which typically consist of paired noisy and noise-free seismic data, are often created synthetically (Yu et al., 2019; Liu et al., 2018; Dong et al., 2019; Wang et al., 2022) because acquiring seismic data to serve as noise-free data is practically unfeasible. Although the supervised method has shown notable effectiveness in denoising synthetic data, its performance is often degraded when applied to field data, mainly because of the differences between the synthetic and actual observed data. Several studies (Zhao et al., 2018; Brusova et al., 2021; Cheng et al., 2023a; Dong et al., 2023) have attempted to enhance network training by extracting

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noise from the observed field data and integrating it into synthetic data. Although these methods potentially improve the denoising performance to some degree, a notable data bias remains between the synthetic and field data. The scarcity of ground truth data has often become a major challenge in denoising tasks. However, in the field of computer vision, an elegant solution to this problem called Noise2Noise (N2N) has been developed (Lehtinen et al., 2018). The N2N strategy utilizes pairs of independent noisy measurements of the same target instead of using pairs of noisy and clean measurements. Under certain noise distribution conditions, DNNs trained by N2N can infer clean data. Lapins et al. (2024) met the requirements for independent pairs of noisy Distributed Acoustic Sensing (DAS) measurements by splicing two fibers hosted within a single optical cable that recorded the same underlying signal corrupted by different observational noises. Wang and Zhang (2021) applied N2N to numerical shot data to attenuate seismic noise and provided a quantitative evaluation compared with conventional denoising methods such as Band-pass and F-X deconvolution. The most direct method of applying the Noise2Noise method to seismic data processing is to utilize pairs of repeated raw shot data at the same point (Shao et al., 2022). However, notably, accessing seismic data is fundamentally challenging. Opportunities for processing data before vertical stacking are limited because

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vendors typically perform desweeps and vertical stacking automatically to reduce data volume. Therefore, although N2N eliminates the requirement of clean training targets for more practical applications, researchers have tended to develop N2N-based self-supervised methods that do not require two independent noisy real measurements for DNN training. An N2N-based denoising approach with only a single noisy measurement can be achieved through self-supervised learning, which employs a sampling or subsampling strategy to generate pairs of noisy measurements (Huang et al., 2021; Shao et al., 2022; Zhao et al., 2023). Some studies have used conventional seismic denoising methods to provide target data for noisy field data (Yu et al., 2019; Mandelli et al., 2019; Wang et al., 2019; Shan et al., 2021, Yang et al., 2023). Another approach is to generate a noisier sample by directly adding noise to already noisy data (Moran et al., 2020; Zhang et al., 2022; Cheng et al., 2023b; Li et al., 2024). The added noise can be extracted from observed field data or sampled from a predefined noise distribution based on prior knowledge. However, while a DNN trained on these noisier samples gains the ability to denoise, bias exists between noisier and noisy pairs and noise-clean pairs. This bias can significantly affect DNN denoising performance when applied to noisy raw data. Wang et al. (2023) utilized high self-similarity in the horizontal direction of common reflection gathers following a normal

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move-out correction to generate a paired noisy dataset. Song et al. (2023) proposed Shot2Shot (S2S) with a re-de-noising regularization method, which uses the pair of a shot gather and its neighboring shot gather for DNN training. The similarity, yet distinct differences, between a shot gather and its neighbor can lead to a rough estimation result. To address this issue, they incorporated a re-de-noising regularization term into the loss function of the DNN.

To address the challenge of noise reduction in single noisy measurement scenarios, several unsupervised deep learning methods have been developed in addition to the N2N strategy. Autoencoders (AEs) can preserve subtle data features while removing random noise through unsupervised learning manner. The denoising ability of AEs has been demonstrated in seismic domains (Chen et al., 2019; Zhang et al., 2019b; Saad and Chen, 2020; Song et al., 2020). The blindspot strategy (Krull et al., 2019) has been proven to effectively attenuate random noise in seismic data in a self-supervised manner (Birine et al., 2021a, 2021b; Liu et al., 2023; Birine and Ravasi, 2024). Ma et al. (2023) proposed an Attention Cycle GAN Network (ACGNet) for unpaired training, which was trained using a diverse hybrid training set that included both noisy and synthetically generated clean data. The model learns the transformation from a noisy domain to a clean domain by focusing on a domain-wide rather than a one-to-one

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sample transformation. The Deep Image Prior (DIP) technique (Ulyanov et al., 2020) does not require labeled clean data for denoising, leveraging the principle that DNNs minimize the loss function during training by initially fitting predictable signals. Specifically, the structural signals are more predictive than the unstructured noise signals. In addition, low-frequency components tend to be predicted before high-frequency components (Rahaman et al., 2019; Xu et al., 2019). Utilizing these characteristics, the DNN at an optimal number of training epochs focuses on learning only the coherent and relatively low-frequency signal components, thereby achieving a denoising effect. Zhang and Wang (2023) demonstrated that a DIP-based recursive denoising method with improved quality control criteria could effectively attenuate seismic noise.

As previously mentioned, several proposed methods have already used conventional seismic denoising methods to provide target data (henceforth referred to as pseudo-denoised data) for N2N requirements (Yu et al., 2019; Mandelli et al., 2019; Wang et al., 2019; Shan et al., 2021; Yang et al., 2023). However, in these studies, conventional denoising methods were solely utilized in the post-stack domain or common shot domain (CSD). Subsequently, the DNN was trained in the same domain where denoising was performed by pairing the original noisy data with the pseudo-denoised data. During the denoising process, noise prediction relies on

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information from the applied domain. According to the Universal Approximation Theorem (Cybenko, 1989), if a DNN is fed with the same information as that used for conventional denoising, a well-trained DNN can approximate the mapping of these conventional denoising methods. This implies that the residual noise in pseudo-denoised data can be predicted using the original noisy data. In reality, owing to the inherent inductive biases in DNNs, which are particularly noticeable in Convolutional Neural Networks (CNN), and regularization techniques such as Dropout and Early Stopping, the DNNs do not fully learn from the training data. This leads to a tendency to preferentially predict more easily predictable signals like the DIP method, which results in some level of noise reduction. However, this approach causes DNNs to focus on imitating the results of conventional denoising methods. Consequently, they inherit the limitations of these methods, resulting in limited improvements in the SNR. Notably, because the inference phase of the DNN tends to be efficient, this strategy is beneficial for reducing the computational cost of estimating the denoised gather (Mandelli et al., 2019).

This study introduced the Noise2Noise enhancement (N2NE) framework, which improves existing noise reduction methods in seismic processing. We adopted the N2NE framework under two scenarios: one with repeated shots at the same point and one without. In

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scenarios involving repeated shots at the same point within the N2NE framework, the DNN was trained using a pair of repeated data before stacking. N2N enhances the effectiveness of denoising in traditional stacking techniques by utilizing statistical insights from an entire dataset. As mentioned earlier, the concept of applying N2N to repeated shots is not novel; however, few quantitative evaluations have been conducted. This study represents an early attempt to quantitatively assess the performance of N2N in comparison to conventional stacking methods for actual field noise. Additionally, we introduced the “substack” strategy as a novel approach to address extremely noisy data in this case. In a scenario without repeated shots at the same location within the N2NE framework, existing denoising methods were used to generate pseudo-denoised data, similar to previous studies. However, the key difference between our N2NE framework and a previous study is that we employed existing denoising methods within the common receiver domain (CRD) rather than the CSD. Consequently, the obtained pseudo-denoised data, including information on adjacent shot points, resulted in residual noise that was not predictable from the original single-shot data. Therefore, N2N learning can be effective without directly replicating existing denoising methods. The N2NE framework in these two

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cases was quantitatively evaluated to improve the denoising effectiveness of the existing methods using a pseudo-noise record that added synthetic seismic and field noise data.

METHODS

Noise2Noise Theory

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In seismic data processing, the observed seismic data $\boldsymbol{x}$ are composed of the underlying useful signals $\boldsymbol{s}$ and additive noise $\boldsymbol{n}$, represented as follows:

$$\boldsymbol{x} = \boldsymbol{s} + \boldsymbol{n}. \quad (1)$$

In traditional DNN-based denoising methods, the observed noisy signal $\boldsymbol{x_i}$ and the corresponding clean signal $\boldsymbol{y_i}$ are used as the input and output, respectively, for training. The DNNs learn the approximated mapping function f_θ, parameterized by the model weights θ, from noisy data $\boldsymbol{x_i}$ ground-truth data $\boldsymbol{y_i}$ by minimizing the expected loss calculated using the loss function $\mathcal{L}$:

$$\arg\min_{\theta} \sum_{i} \mathcal{L}(f_\theta(\boldsymbol{x}_i), \boldsymbol{y}_i). \quad (2)$$

The N2N framework utilizes the principle that replacing targets with random numbers does not change the estimation as long as their expectations match those of the targets; the estimate remains unchanged (Lehtinen et al. 2018). This implies that training DNNs with observed data $\boldsymbol{x}_i'$ contaminated by zero-mean noise instead of using ground-truth signals as labels, DNNs can learn noise reduction by minimizing the following equation:

$$\underset{\theta}{\arg min} \sum_{i} \mathcal{L}\left(f_{\theta}(\boldsymbol{x}_i), \boldsymbol{x}_i'\right). \qquad (3)$$

Note that the underlying signals in the $\boldsymbol{x}_i$ and $\boldsymbol{x}_i'$ are identical, which means $\boldsymbol{x}_i = \boldsymbol{y}_i + \boldsymbol{n}$, $\boldsymbol{x}_i' = \boldsymbol{y}_i + \boldsymbol{n}'$, where $\boldsymbol{n}$ and $\boldsymbol{n}'$ are independent noises.

Processing flow of Repeated Shot Acquisition Scenario

Figure 1 shows a comparison of the processing flows between conventional stacking methods and stacking with the N2NE framework under repeated shot acquisition scenarios. As N2N eliminates the need for clean training targets, we can directly use a pair of repeated shots as training data to optimize the DNN model. In the inference phase, the trained DNN model is applied to each prestacked shot for denoising. The resulting pre-stacked denoised shots are stacked to produce the final denoised shot. Figure 2 shows the processing flow of the N2NE

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framework for scenarios in which repeated shots were not available. In this scenario, creating a pseudo-denoised image is necessary. To generate pseudo-denoised data, we employed a conventional denoising method within the CRD. The DNN model was then trained using pairs of generated pseudo-denoised shots and original noisy data. Finally, applying the trained DNN to the original noisy data resulted in a denoised shot that enhanced the noise suppression effect of the conventional denoising method. In this process, to satisfy the N2N requirement, the residual noise in the pseudo-denoised shot must be random relative to the original noisy shot. The pseudo-denoised data generated through the CRD operation included random noise information from adjacent shots. Therefore, we expect that noise reduction operations in CRD will result in a higher randomness of the residual noise in relation to the noise in the original data compared with the CSD operation. Consequently, N2N can be effectively applied to pseudo-denoised data generated in CRD.

Denoising Architecture

For the denoising network, we used the U-shaped fully convolutional network (U-net) (Ronneberger et al., 2015). Figure 3 shows a schematic of the U-net architecture of the proposed

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method, which features four encoders (downsampling), four decoders (upsampling), and an output layer. Each encoder stage comprised a convolutional layer with strides of one (flat convolution) and two (downsampling convolution). The decoder stages included both a flat convolutional layer and bilinear upsampling layer. At every downsampling and upsampling stage, the number of feature maps was doubled and halved, respectively. The initial convolution layer contained 32 feature maps. Following each convolution, the output underwent batch normalization (Ioffe and Szegedy, 2015) and was processed using a rectified linear unit (ReLU). Additionally, skip connections were employed to merge the intermediate outputs of each encoder stage with the inputs of the corresponding decoder stage, thereby enhancing feature retention. The final output was obtained after a flat convolution following the encoder and decoder stages. Throughout the study, the network was optimized to minimize the mean absolute error (MAE) loss function using the adaptive moment estimation (Adam) optimizer (Kingma and Ba, 2015) with a learning rate of $1.0 \times 10^{\wedge -4}$. In all cases, the batch size was set to 2, and the maximum number of epochs was 200. During the model-training phase, 10% of the dataset was allocated for validation. Early stopping was implemented if the MAE of the validation data did not

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improve after > five consecutive epochs. For implementation, we used the PyTorch framework and conducted training on a Tesla V100S graphics processing unit.

EXPERIMENT AND RESULT

Preparing Pseudo-noise data

To conduct a quantitative evaluation, we created pseudo-noise data by combining synthetic seismic data with actual field noise. Synthetic seismic data, which served as the ground-truth signal, were derived from the Marmousi model. Field noise was extracted from downhole monitoring data acquired by the DAS in the Utah FORGE project (Martin and Nash, 2019). The pseudo-noise record consisted of 801 shots and 801 receivers, with both the receiver and shot intervals of 25 m in the Marmousi dataset. Although the spatial sampling of the Utah Forge DAS data was 1.02 m, and the sampling intervals were inconsistent relative to the Marmousi model, we combined the two datasets to generate the synthetic noise data, disregarding this discrepancy for simplicity. To evaluate the effect of different noise levels, the field noise was scaled by factors of 0.02, 0.04, 0.08, and 0.16, resulting in an average peak signal-to-noise ratio (PSNR) of the pseudo-noise data with scale factors of 30.93, 24.91, 18.89, and 12.87, respectively. During the DNN training phase, horizontal flip data augmentation was employed to increase the dataset diversity.

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Repeated Shot Acquisition Scenario

To simulate repeated shot acquisition, field noise recorded at different times was added to the single-shot gathers from the Marmousi model. Three stacking fold numbers (2, 4, and 8) were used as test cases to compare the conventional stacking and our proposed N2NE stacking. In the N2NE framework, the DNNs were trained using pairs of repeated shots. If there were more than two repeated shots, a combination of the two pairs was randomly selected from the sets for each training iteration. The trained DNNs were then applied to repeated shots, and the generated denoised repeated shots were stacked. For comparison, we applied straight stacking and diversity stacking. To quantitatively compare the quality of the denoised results with the corresponding ground truth data, we utilized two performance metrics: the PSNR and structural similarity index measure (SSIM) (Wang et al., 2004). Figure 4 shows the noise attenuation results of N2NE stacking and diversity stacking for various fold numbers. A large amount of high-amplitude tracewise and horizontal noise significantly covered the ground truth signal (Figure 4a). For diversity stacking (Figures 4g-4j), the background noise remained visible even with 16 folds (Figure 4j). However, in N2NE stacking (Figures 4c-4f), the noise was effectively removed by as few as two folds (Figure 4c). The results, including the PSNR and SSIM values,

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are presented in Table 1. Our proposed N2NE framework consistently improves the PSNR and SSIM compared with the conventional stacking approach across all test cases.

We performed sensitivity analysis based on the size of the training dataset to investigate the robustness of the proposed method against a limited amount of training data. For this analysis, we prepared datasets with 200, 400, 600, and 800 shot-gather pairs, each with two folds. These shot gathers were extracted from the Marmousi model to decrease the shot point number rather than through random or equally spaced extraction, assuming that the actual data acquisition is performed sequentially. The results of the sensitivity analyses are presented in Table 2. It is evident from the analysis that the size of the shot gather dataset significantly affects the effectiveness of the N2NE framework, with smaller datasets resulting in reduced denoising. However, even with a small dataset size of 200, the N2NE method outperformed the conventional diversity stack method.

Substack Strategy

Thus far, the results have demonstrated that the N2NE framework enhances the denoising effect compared with conventional stacking methods. However, Table 1 shows that the N2NE

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framework has limited improvement in the evaluation metrics compared with traditional stacking methods when the fold number is increased. For example, at a noise level of 0.16, increasing the fold number from 2 to 16 leads to a PSNR improvement factor of 1.59 with the diversity stack, whereas the N2NE stack resulted in a more modest improvement factor of 1.08. To improve the denoising effect of the N2NE stack when a large number of folds are used, we proposed a substack strategy. In this strategy, instead of directly using pairs of repeated shots to train the DNN, the shot data were stacked with a small fold number (substack), and the DNN was trained using pairs of substacked data with noise suppression (Figure 5). The substack was performed at each iteration of DNN training with a random combination of repeated shots. Figure 6 shows the results of using the substack strategy with 16 repetitive shots, where the fold numbers utilized for the substack were 2, 4, and 8. The evaluation metrics improved with the substack strategy, exhibiting the best results when the number of substack folds was eight. Without the substack strategy, some reflected waves were damaged (Figure 6c); however, the N2NE stack with the substack strategy recovered the reflected waves more accurately (Figure 6k). The findings of this study indicate that integrating the substack strategy into the N2NE framework overcomes the limited improvements in noise suppression with an increasing number of folds.

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Without Repeated Shot Acquisition Scenario

In the scenarios without denoising, conventional denoising methods were applied within the CRD to generate pseudo-repeat shots. The generated pseudo-denoised shots were then paired with the original shots to train the DNN in the N2NE framework. We employed F-X deconvolution, a median filter, and a blind-trace network (Liu et al., 2023) as the conventional methods. To evaluate the enhanced denoising capability of the N2NE framework, we compared the results of conventional denoising methods with those achieved using the N2NE framework. A distinctive feature of our N2NE framework was that the denoising process used to generate pseudo-noise data occurred in the CRD, which differs from the CSD, where N2N learning occurred. It is expected that learning in different domains will increase the randomness of the noise components in the pseudo-noise and original data. To validate the effectiveness of this approach, we included a case in which N2N learning was conducted in the CRD (both the denoising process and N2N learning were conducted in the same domain) for comparison. In addition, we utilized shot2shot (S2S) with re-de-noising regularization as an N2N-based denoising method for comparison. The hyperparameters of each conventional method were determined using a grid search (Appendix A). The comparison results, including the PSNR and SSIM values, are listed in Table 3. We confirm that the application of our proposed N2NE framework consistently improves the PSNR and SSIM across all conventional methods. Furthermore, our proposed N2NE framework yields better results than a scenario in which the denoising process and N2N learning are performed in the same domain. Figure 7 shows the

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results of the denoising operation. Although the F-X deconvolution process reduced background noise to a certain degree, some noise remained (Figure 7c, d). The N2NE framework, trained on the pseudo-denoised and original data with residual noise, showed that the residual noise was further reduced, and the PSNR was improved (Figure 7e, f). The Blind-trace network effectively attenuated the background noise, as shown in Figure 2g. However, the difference plots demonstrated some degree of ground truth signal leakage (Figure 7h). The Blind-trace network, enhanced through our proposed N2NE framework, reduced signal leakage while achieving better noise attenuation (Figure 7i, j). Although our reproduction of the Shot2Shot (S2S) method effectively suppressed noise in low-noise-level cases, it resulted in artificial gaps and unstable noise suppression in high-noise-level cases (Figure 7k, l).

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DISCUSSION

The proposed N2NE framework used the statistical noise information from the entire training dataset. Therefore, the volume and diversity of the data were critical factors in enhancing the accuracy of the proposed N2NE method, as demonstrated by the results of the sensitivity analysis of the size of the training data in the repeated-shot scenario. Consequently, although the N2NE framework showed high efficacy in extensive seismic acquisition fields, its effectiveness is limited to small-scale exploration. Transfer learning can be employed to address this limitation. Initially, the DNN was trained on synthetic seismic data or datasets from different regions that provide abundant training data. Subsequently, the weights of the pretrained DNN were used as initial values to fine-tune the model on a smaller dataset specific to the target region. The N2NE framework adds DNN training and inference phases to the conventional denoising method, resulting in a significant computational cost. However, because the computational cost of the inference phase is relatively low if the models trained under the N2NE framework have generalization capabilities for data not included in the training phase, such as data from different surveys, noise suppression might be achievable at a lower computational cost than existing methods. Evaluating the generalization capabilities of models trained with the N2NE framework, particularly their effectiveness in transferring knowledge across different datasets and their potential to reduce computational costs, represents a promising area for future research. This includes assessing the efficacy of transfer learning within the N2NE framework to overcome the limitations associated with small data sizes.

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This study demonstrated the efficacy of the N2NE framework by employing a pseudo-noise dataset that combines synthetic seismic data with field noise. However, this experiment did not address inconsistencies in the sources of the repeated data. We believe that future validation using real records is essential for assessing the applicability of the N2NE framework to actual observational data.

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CONCLUSION

This study introduced the N2NE framework, which was designed to enhance traditional noise suppression algorithms in seismic processing. The N2NE framework was quantitatively evaluated under two scenarios: one with repeated shots at the same point and one without. In scenarios with repeated shots, the N2NE framework enhanced the conventional stacking method using DNNs trained on pairs of repeated shots. Furthermore, it was demonstrated that employing the "Substack strategy" in cases with a large fold number further improved the noise reduction effect. In scenarios without repeated shots, conventional denoising methods were utilized in the CRD to generate pseudo-denoised shots. The resulting pseudo-denoised data were paired with the original noisy shots and used to train the DNN. The optimized trained model had an enhanced capability compared with the conventional denoising method. We believe that this study provides a foundation for future research on N2N-based seismic denoising methods and contributes to improving the quality of seismic records and data acquisition efficiency.

DATA AND MATERIALS AVAILABILITY

Data associated with this research are available and can be accessed via the following URL: https://zenodo.org/doi/10.5281/zenodo.10663472

APPENDICES

APPENDIX A

Hyperparameter search of conventional methods

To demonstrate the effectiveness of the proposed Noise2Noise (N2N) enhancement framework in improving existing noise suppression methods, we used F-X deconvolution, a median filter, and a blind-trace network. Additionally, shot2shot with re-denoising regularization was used as a comparison method based on the same N2N approach. We determined the hyperparameters for each method using a grid search, as listed in Table A-1. For F-X deconvolution, implemented in the seismic exploration processing system "SuperX-C" (manufactured by JGI), we adjusted the spatial operator length of its predictive filter. For the

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median filter implemented in the Python numerical analysis library SciPy (Virtanen et al., 2010), we adjusted the filter length in the temporal and spatial directions. In the blind-trace network (Liu et al., 2023), we used the same U-net architecture as in the N2NE framework (Figure 3). The Mean Absolute Error was used as the loss function, and the loss was calculated across the fully masked trace. The number of noisy traces in the training input data was adjusted as a hyperparameter.

In our implementation of the S2S framework with re-denoising regularization (Song et al., 2023), we used the same U-net architecture as in the N2NE framework. The process involved adding new noise to the denoising output and then removing it, a process termed "re-denoising. Two penalty terms were introduced: stability (L_{stab}) and re-de-noising terms (L_{rede}), which together ensured that the denoiser learned as much valid information as possible from the original image while ensuring that no noise was included in the learned details (For more details, refer to Song et al., 2023). According to Song et al. (2023), we used the following loss function:

$$L_{\mathrm{denoi}} = L_{\mathrm{S2S}} + \gamma_1(\gamma_2 L_{\mathrm{rede}} + L_{\mathrm{stab}}) \qquad \text{(A-1)}$$

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where γ1 weighs S2S loss and re-denoising regularization, and γ2 trades off the re-denoising term and the stability term. We sampled noise from the Poisson distribution for the re-de-noising process. In addition, we tuned the γ1 and the γ2 as hyperparameters.

Table A-1. The hyperparameter search ranges for various conventional methods.

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Method	Hyperparameter	Range
F-X deconvolution	Spatial Operator Length	3, 5, 7, 9, 11
Median Filter	Spatial Filter Length	3, 5, 7, 9, 11
	Temporal Filter Length	3, 5, 7, 9, 11
Blind-trace network	Number of Noisy Traces	20 %, 40 %, 60 %, 80 %
S2S with re-de-noising regularization	γ1	2, 3, 4, 5
	γ2	0.15, 0.25, 0.35, 0.45

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Table 1. Evaluation metrics (PSNR/SSIM) comparison of stacking methods under repeated shots scenario. Bold indicates the highest evaluation metrics.

Noise Scale	Fold Number	Normal Stack	Diversity Stack	N2NE Stack
0.02	2	33.23/0.940	35.08/0.923	**42.68/0.987**
	4	35.99/0.966	38.52/0.960	**44.56/0.992**
	8	38.93/0.977	41.73/0.980	**45.81/0.993**
	16	42.32/0.986	44.89/0.990	**46.24/0.994**
0.04	2	27.21/0.877	29.13/0.797	**38.32/0.961**
	4	29.97/0.931	32.63/0.875	**40.05/0.975**
	8	32.91/0.946	35.87/0.930	**42.13/0.984**
	16	36.30/0.958	39.08/0.963	**41.71/0.982**
0.08	2	21.19/0.846	23.15/0.700	**35.56/0.926**
	4	23.94/0.903	26.69/0.704	**37.24/0.949**
	8	26.89/0.909	29.95/0.800	**37.17/0.949**
	16	30.28/0.908	33.20/0.879	**38.45/0.961**
0.16	2	15.17/0.837	17.15/0.677	**33.10/0.874**
	4	17.92/0.895	20.71/0.610	**34.38/0.906**
	8	20.87/0.892	23.98/0.606	**34.64/0.912**
	16	24.26/0.863	27.26/0.690	**35.68/0.930**

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Table 2. Evaluation metrics (PSNR/SSIM) comparison of N2NE stacking methods under different data sizes.

NoiseLevel	Data Size		
	200	400	801
0.02	36.63/0.967	39.37/0.98	44.15/0.989
0.04	34.76/0.942	37.22/0.963	38.32/0.961
0.08	32.87/0.894	35.05/0.934	35.56/0.926
0.16	29.62/0.717	30.08/0.756	33.1/0.874

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Table 3. Evaluation metrics (PSNR/SSIM) comparison for conventional denoising methods, with and without the N2NE framework, as well as the S2S method, in a repeated shots scenario. N2NE(CRD) means the case of N2N learning is conducted in CRD. Bold indicates the highest evaluation metrics, while underscore denotes the highest metrics among identical conventional methods.

Noise Scale	0.02	0.04	0.08
Original Noisy Shot	30.93/0.885	24.91/0.807	18.89/0.788
F-X-deconvolution	38.36/0.967	33.59/0.901	28.41/0.761
N2NE F-X deconvolution (Proposed)	**41.68**/**0.979**	37.91/0.948	33.72/0.865
N2NE F-X deconvolution (CRD)	41.21/**0.979**	37.58/0.945	33.48/0.856
Median Filter	34.17/0.920	31.71/0.819	27.68/0.673
N2NE median Filter (Proposed)	35.30/0.948	33.76/0.890	31.02/0.751
N2NE median Filter (CRD)	34.74/0.931	32.45/0.838	28.74/0.675
Blind-trace network	38.53/0.971	36.73/0.956	33.66/0.924
N2NE blind-trace network (Proposed)	40.21/0.977	**38.08**/**0.962**	**35.07**/**0.937**
N2NE blind-trace network (CRD)	39.49/0.975	37.73/0.960	34.99/0.935
S2S with re-de-noising regularization	39.34/0.970	35.62/0.922	31.67/0.840

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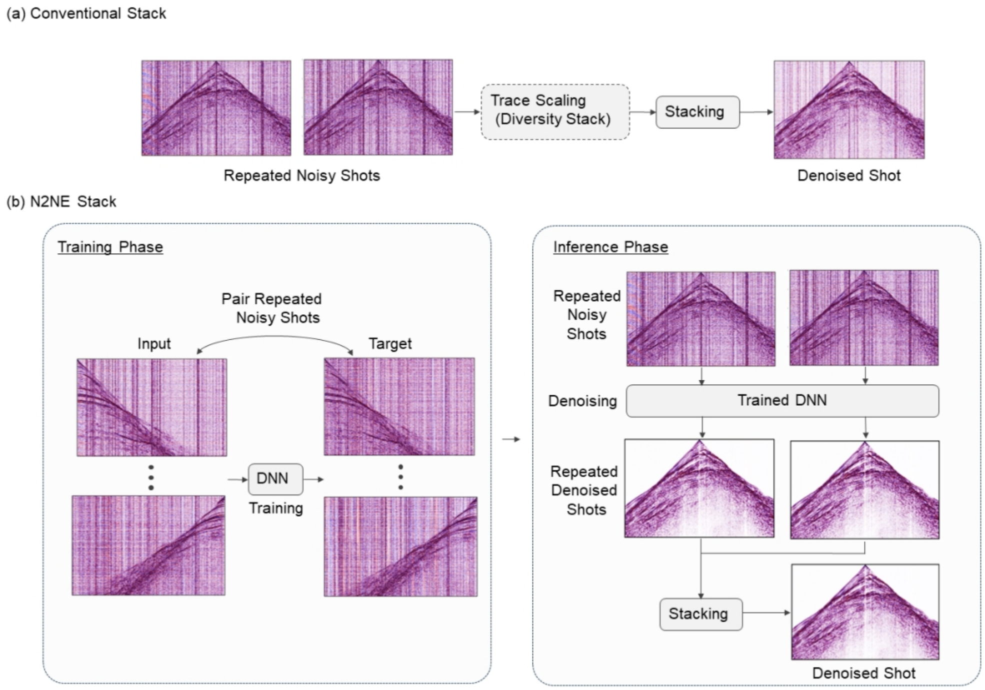

Figure 1. Flowchart of conventional (a) and N2NE stacks (b) under a repeated shot scenario.

898x673mm (38 x 38 DPI)

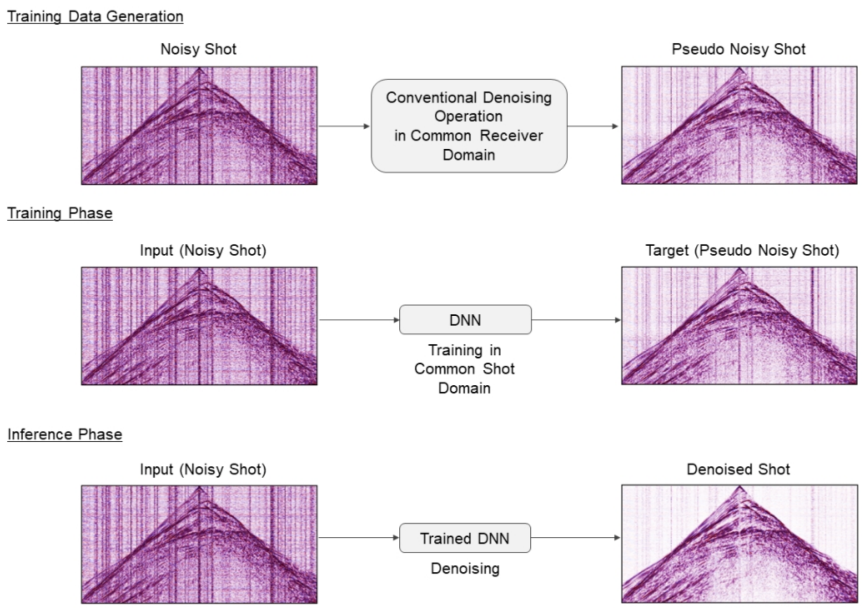

Figure 2. Flowchart of N2NE framework without a repeated shot scenario.

898x673mm (38 x 38 DPI)

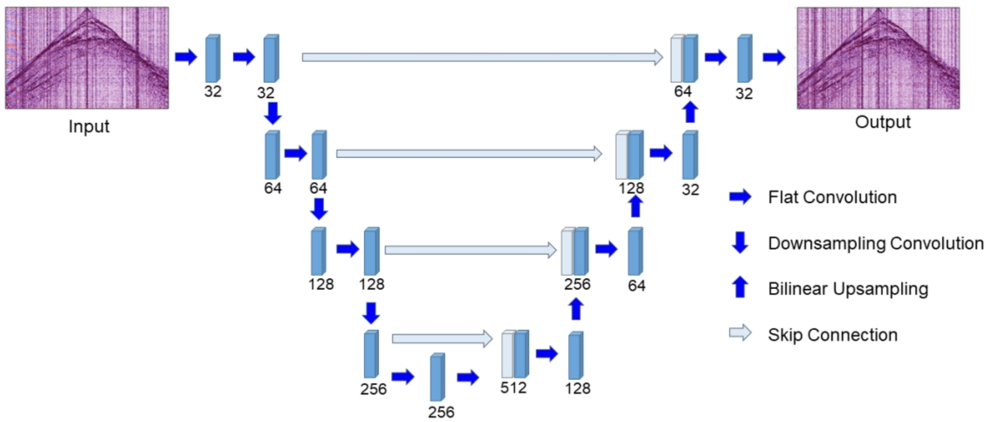

Figure 3. Schematic U-net architecture in this study. The integer number represents the number of feature maps of convolution layers. Except for the last convolution layer, the convolution outputs were applied for batch normalization and passed through a ReLU. Final output passing through the sigmoid layer to be normalized.

898x673mm (38 x 38 DPI)

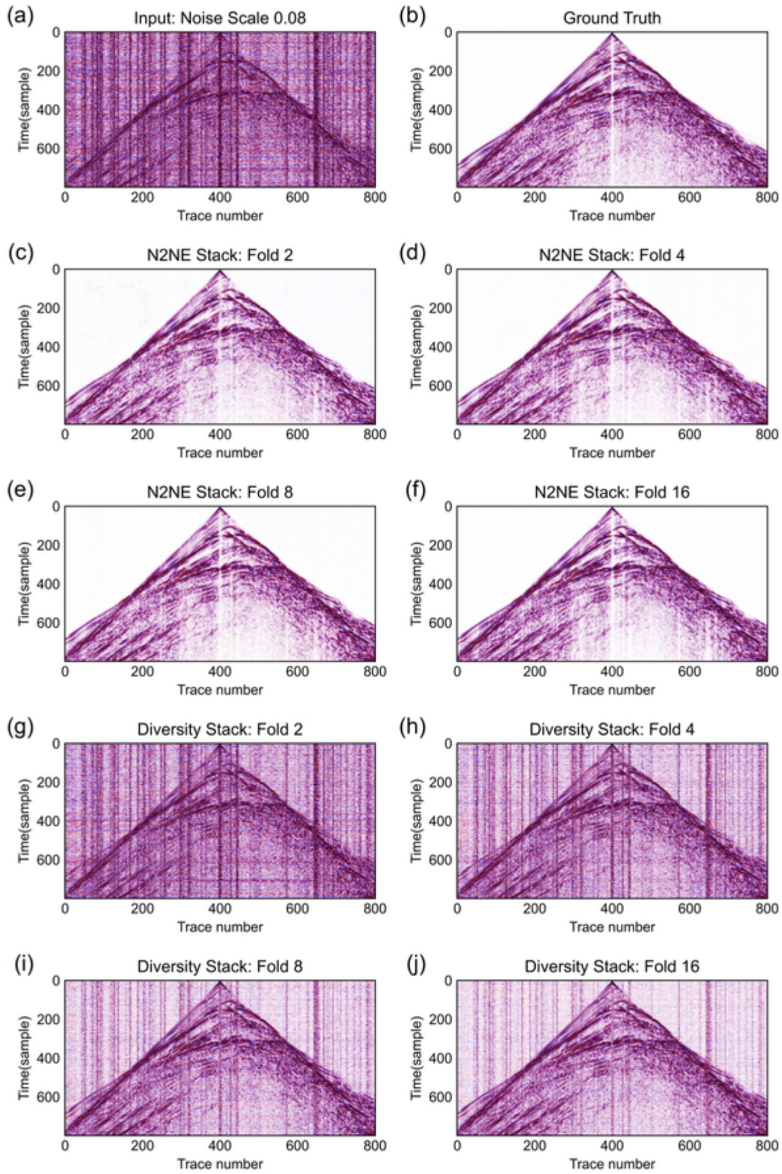

Figure 4. Denoising results under a repeated shot scenario. (a) Noisy shot gather. (b) Ground truth shot gather. (c-f) N2NE stack results with different fold numbers. (g-j) Diversity stack results with different fold numbers.

51x77mm (300 x 300 DPI)

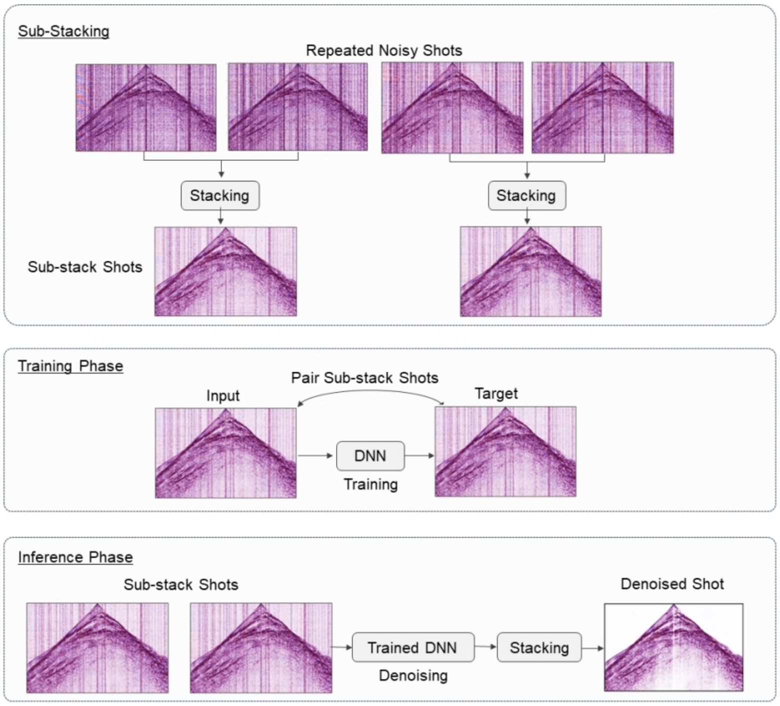

Figure 5. Flowchart of N2NE stack with the substack strategy.

898x673mm (38 x 38 DPI)

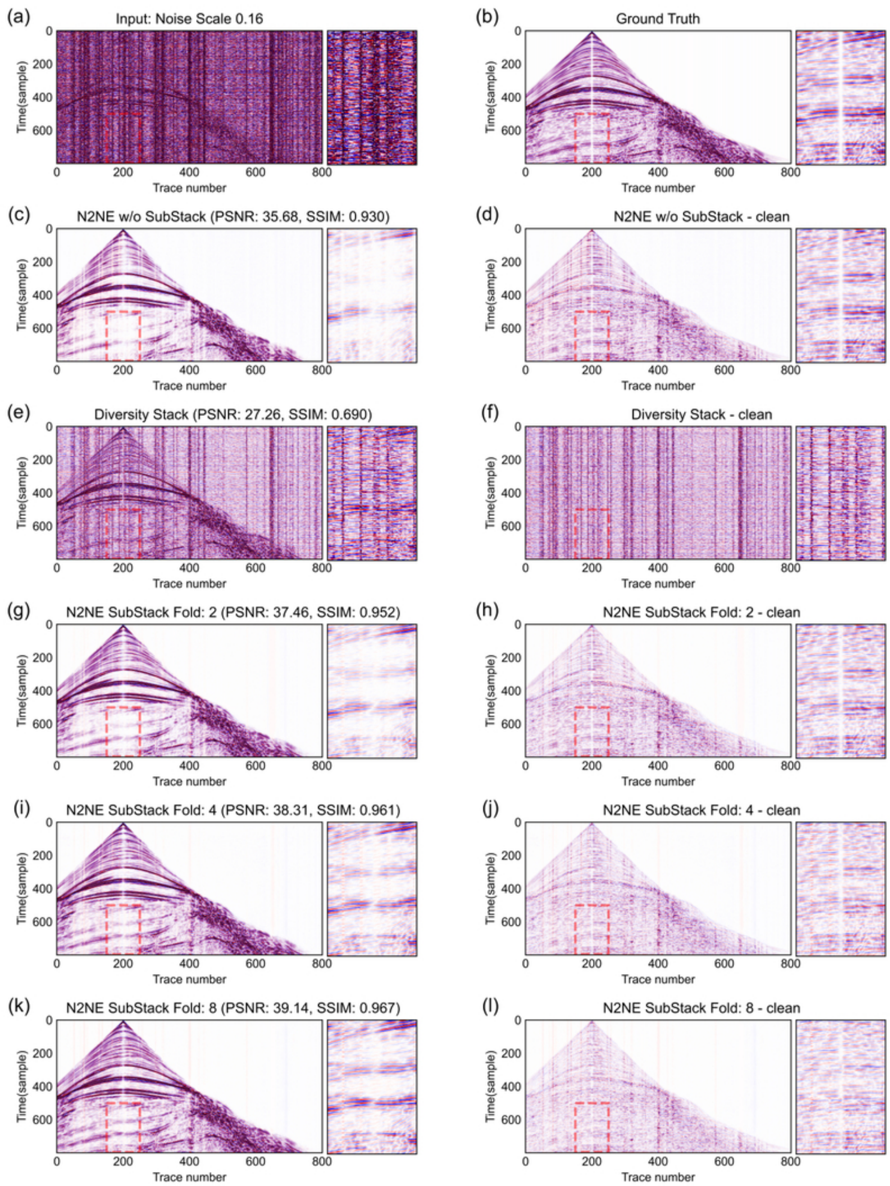

Figure 6. Denoising results of different stack methods with 16 repetitive shots. (a) Noisy shot gather. (b) Ground truth shot gather. Denoising results and signal leakage of N2NE stack without substack (c, d), diversity stack (e, f), and N2NE stack with different substack fold numbers(g-l), respectively. The areas within the red dotted rectangles are shown enlarged.

74x90mm (300 x 300 DPI)

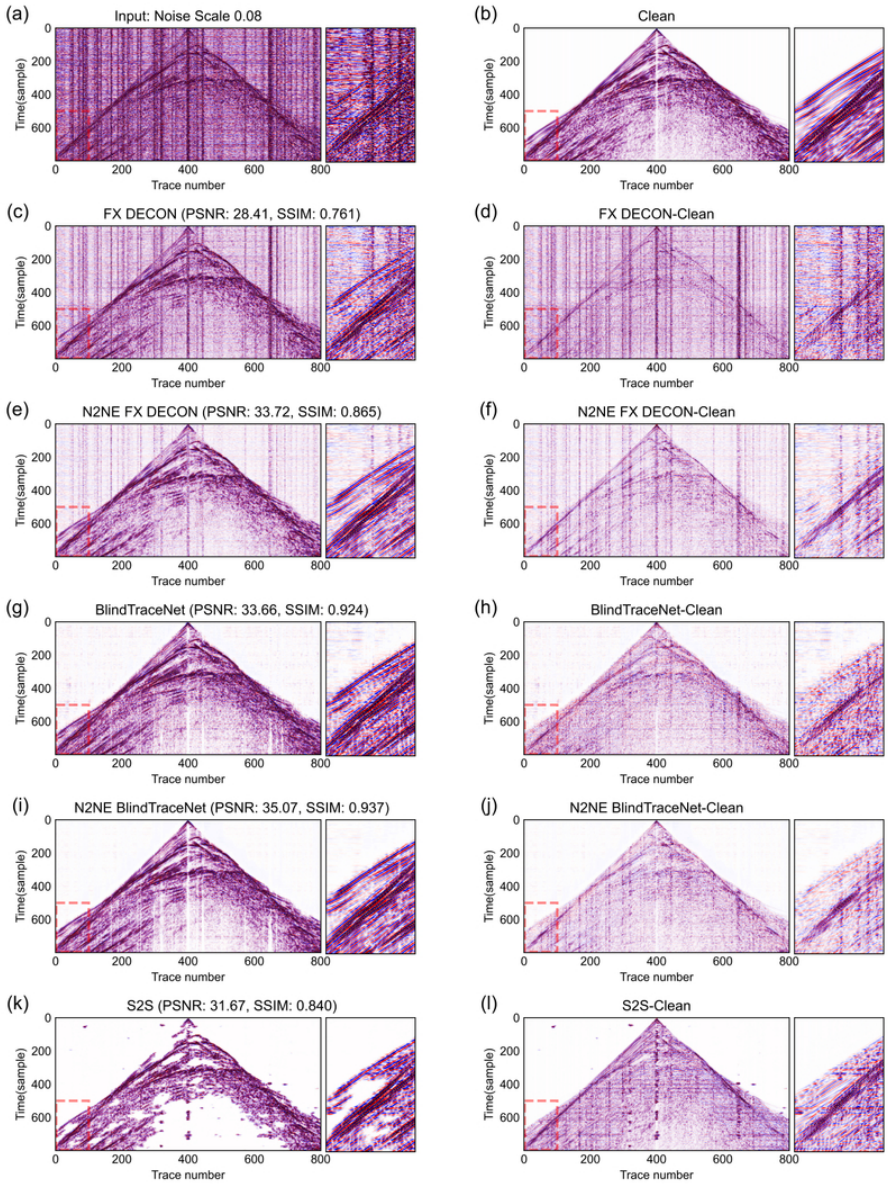

Figure 7. Denoising results in the absence of repeated shot scenarios. (a) Noisy shot gather. (b) Ground truth shot gather. Denoising results and signal leakage by F-X deconvolution (c, d), N2NE F-X deconvolution (e, f), Blind Trace Network (g, h), N2N Blind Trace Network (i, j), and Shot2Shot with Re-denoising Regularization (k, l). The areas within the red dotted rectangles are shown enlarged.

74x90mm (300 x 300 DPI)