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Robust Seismic data denoising via self-supervised deep learning

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Summary

Seismic data denoising is a critical component of seismic data processing, yet effectively removing erratic noise, characterized by its non-Gaussian distribution and high amplitude, remains a substantial challenge for conventional methods and deep learning (DL) algorithms. This paper introduces a novel zero-shot unsupervised DL framework designed specifically to mitigate erratic noise, with a particular emphasis on blending noise. Drawing inspiration from Noise2Noise and data augmentation principles, we present a robust self-supervised denoising network named “Robust Noiser2Noiser." Our methodology generates two independent re-corrupted datasets from the original noisy dataset, using one as the input and the other as the training target. Subsequently, we employ a deep-learning-based denoiser, DnCNN, for training purposes.

Introduction

Seismic data denoising stands as a fundamental pillar in the realm of seismic data processing. In this paper, we introduce a pioneering self-supervised framework designed to address erratic noise, specifically focusing on mitigating blending noise in simultaneous source acquisition data. Drawing inspiration from Noise2Noise (Lehtinen et al., 2018) and data augmentation methods, we present a robust variant called robust Noiser2Noiser, which is capable of attenuating erratic noise. Our framework operates in a zero-shot, self-supervised manner, eliminating the need for data other than the original noisy dataset. This approach involves independently re-corrupting the original noisy data to generate two independent re-corrupted datasets, using one as the training input and the other as the training label. Subsequently, we employ a commonly used denoising convolutional neural network DnCNN (Zhang et al., 2017) to train the input and label pairs. The specific re-corruption method depends on the type of noise being addressed. For erratic noise, we utilize a robust ℓ_1 norm loss function instead of the conventional mean-square error (MSE) loss function.

Theory

Traditionally, the training of denoising networks has heavily relied on accessing paired datasets containing noisy and clean data for supervised learning. However, a significant breakthrough in this paradigm emerged with the introduction of Noise2Noise by Lehtinen et al. (2018). This pioneering work demonstrated that denoising networks trained on noisy/noisy image pairs can perform remarkably close to those trained on noisy/clean data pairs from the same dataset.

Let’s consider $\mathbf{x}$ as our representation of clean data. The noisy data $\mathbf{y}$ can be expressed as

$$\mathbf{y} = \mathbf{x} + \mathbf{n}, \tag{1}$$

here, $\mathbf{n}$ can be either random noise or erratic noise.

As previously discussed, denoising networks perform similarly when trained on noisy/noisy image pairs compared to noisy/clean data pairs from the same dataset. The question is how to construct a pair of noisy datasets $\mathbf{y}_1$ and $\mathbf{y}_2$ with independent noise from a single noisy dataset $\mathbf{y} = \mathbf{x} + \mathbf{n}$.

Methods such as 'Noiser2Noise' (Moran et al., 2020) and 'Noisy-as-Clean' (Xu et al., 2020) utilize a noisier image as input, where they synthesize noise $\mathbf{z}$, and then train the denoising network on the dataset pair $(\mathbf{y}+\alpha\mathbf{z},\mathbf{y})$. Meanwhile, Pang et al. (2021) trained the denoising model on the pair $(\mathbf{y}+\alpha\mathbf{z},\mathbf{y}-\mathbf{z}/\alpha)$, which results in a loss function more statistically connected to the supervised approach. We have tested both augmentation methods and found the results are very close. For our robust Noiser2Noiser Seismic Denoising Network, we adopt the same method as Pang et al. (2021). In all our tests, we use $\alpha=0.5$, which means the training pair we use is $(\mathbf{y}+0.5*\mathbf{z},\mathbf{y}-2*\mathbf{z})$. Additionally, we employ a symmetric loss function (Chen and He, 2021) to train a Siamese network. The loss function is then defined as:

$$\text{argmin}\frac{1}{2}E \parallel F_\phi(\mathbf{y}_1)-\mathbf{y}_2 \parallel_2^2 + \frac{1}{2}E \parallel F_\phi(\mathbf{y}_2)-\mathbf{y}_1 \parallel_2^2 . \tag{2}$$

Our experiments have demonstrated that employing the residual learning technique, as introduced by Zhang et al. (2017), leads to notable enhancements in denoising performance. With residual learning, the network is trained to optimize against the noise component rather than the raw image data. Consequently, this approach transforms the final loss function into:

$$\text{argmin}\frac{1}{2}E \parallel \mathbf{y}_1-F_\phi(\mathbf{y}_1)-\mathbf{y}_2 \parallel_2^2 + \frac{1}{2}E \parallel \mathbf{y}_2-F_\phi(\mathbf{y}_2)-\mathbf{y}_1 \parallel_2^2 . \tag{3}$$

In the case of a dataset with erratic noise, we replace the ℓ_2 norm with ℓ_1 to make the loss function more robust:

$$\text{argmin}\frac{1}{2}E \parallel \mathbf{y}_1-F_\phi(\mathbf{y}_1)-\mathbf{y}_2 \parallel_1^1 + \frac{1}{2}E \parallel \mathbf{y}_2-F_\phi(\mathbf{y}_2)-\mathbf{y}_1 \parallel_1^1 . \tag{4}$$

Now that we have our training input and target pairs and the corresponding loss functions, the next crucial step is selecting the network architecture. The proposed Robust Self-Supervised denoising framework is compatible with various network architectures, such as ResNet (He et al., 2016), denoising convolutional neural network (DnCNN) (Zhang et al., 2017), and U-net (Ronneberger et al., 2015). In this study, we opt for DnCNN due to its straightforward architecture and effective residual learning strategy.

Example

We now apply our robust Noiser2Noiser framework to a complex 2-D synthetic seismic shot generated using the finite difference method. As depicted in Figure 1a and 1b, we present the clean data and the shot gather with blended noise. The signal-to-noise ratio (SNR) for the noisy shot gather is measured at -1.21 dB. To create the necessary training input and labels, we introduce random time shifts during the blending process, yielding the re-blended training input and labels showcased in Figure 1c and d.

Subsequently, Figure 1e and 1f showcase the deblending results alongside error comparisons with the original clean shot gather. Notably, our approach leads to a remarkable improvement in the SNR, from –1.21 dB to an impressive 21.2 dB.

Conclusion

We introduce a novel zero-shot self-supervised framework designed to mitigate erratic noise effectively. In line with the foundational concept of Noise2Noise, we aim to reduce the dependency on clean training data. Our method employs a pair of re-corrupted datasets during the training process. Notably, even without clean training data, our self-supervised method achieves noteworthy deblending results.

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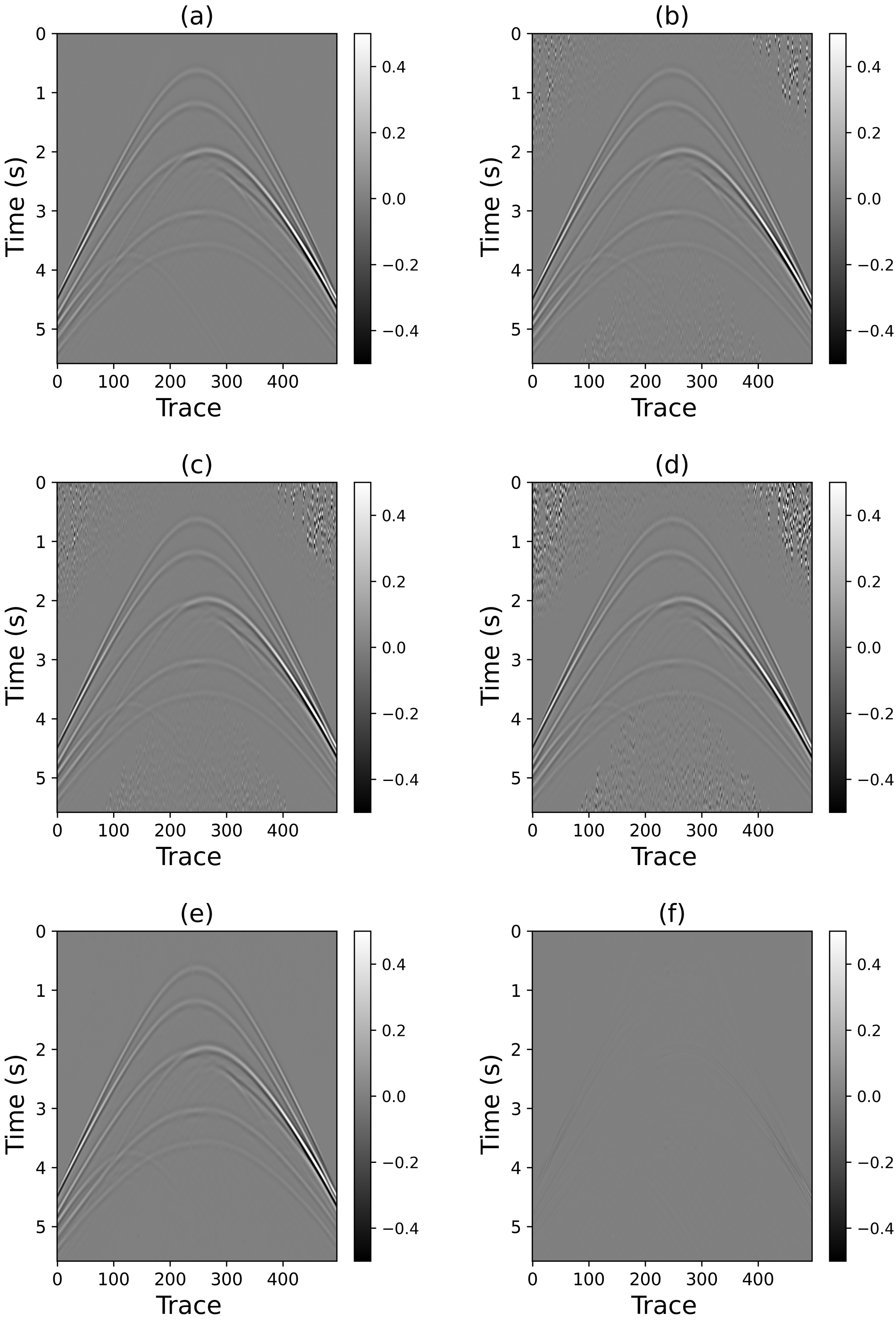

Figure 1: 2-D finite difference synthetic example. (a) Clean data. (b) Noise data with blended noise (SNR=–1.21 dB). (c) Re-corrupted training input. (d) Re-corrupted training label. (e) Deblended result by the robust Noiser2Noiser Network (SNR=21.2 dB). (f) Errors between deblended results and clean data.