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Robust Seismic data denoising via zero-shot unsupervised deep learning

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Abstract

Drawing inspiration from Noise2Noise and data augmentation principles, we present a robust self-supervised denoising network named "Robust Noiser2Noiser." Our approach eliminates the need for paired noisy and clean datasets as required by supervised methods or paired noisy datasets as in Noise2Noise (N2N). We apply our proposed network to both synthetic and real marine data examples, demonstrating significantly improved noise attenuation performance compared to traditional denoising methods and state-of-the-art unsupervised learning methods.

Introduction

In this paper, we introduce a self-supervised framework designed to address both random and erratic noise, with a specific focus on mitigating blending noise in simultaneous source acquisition data. 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.

Methods

Consider a scenario where we have a pair of noisy data samples,

$$\mathbf{y}_1 = \mathbf{x} + \mathbf{e}_1,$$
$$\mathbf{y}_2 = \mathbf{x} + \mathbf{e}_2,$$

with $\mathbf{e}_1$,$\mathbf{e}_2$ representing independent noise sources. A network F_ϕ is then trained to minimize the Noise2Clean Mean Squared Error (MSE) loss function:

$$\begin{aligned}&\operatorname{argmin} E\{\| F_\phi(\mathbf{y}_1) - \mathbf{x} \|_2^2\} \\ &= \operatorname{argmin} E\{\| F_\phi(\mathbf{y}_1) \|_2^2 - 2\mathbf{x}^T F_\phi(\mathbf{y}_1)\}.\end{aligned}$$

Additionally, Noise2Noise employs a similar approach but with a different loss function:

$$\begin{aligned}&\operatorname{argmin} E\{\| F_\phi(\mathbf{y}_1) - \mathbf{y}_2 \|_2^2\} \\ &= \operatorname{argmin} E\{\| F_\phi(\mathbf{y}_1) \|_2^2 - 2\mathbf{x}^T F_\phi(\mathbf{y}_1) - 2\mathbf{e}_2^T F_\phi(\mathbf{y}_1)\}.\end{aligned}$$

Notably, when $\mathbf{e}_1$ and $\mathbf{e}_2$ are independent, the term $2\mathbf{e}_2^T F_\phi(\mathbf{y}_1)$ simplifies to 0. Consequently, the MSE loss functions for Noise2Clean and Noise2Noise yield equivalent results. In our method, we trained the denoising model on the pair $(\mathbf{y} + \alpha\mathbf{z}, \mathbf{y} - \mathbf{z}/\alpha)$, where $\mathbf{z}$ is the synthesized noise which is the same type as $\mathbf{e}$. Additionally, we employ a symmetric loss function and residual learning technique. 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.

Examples

Figure 1 shows the denoising result of 2-D finite difference synthetic example.

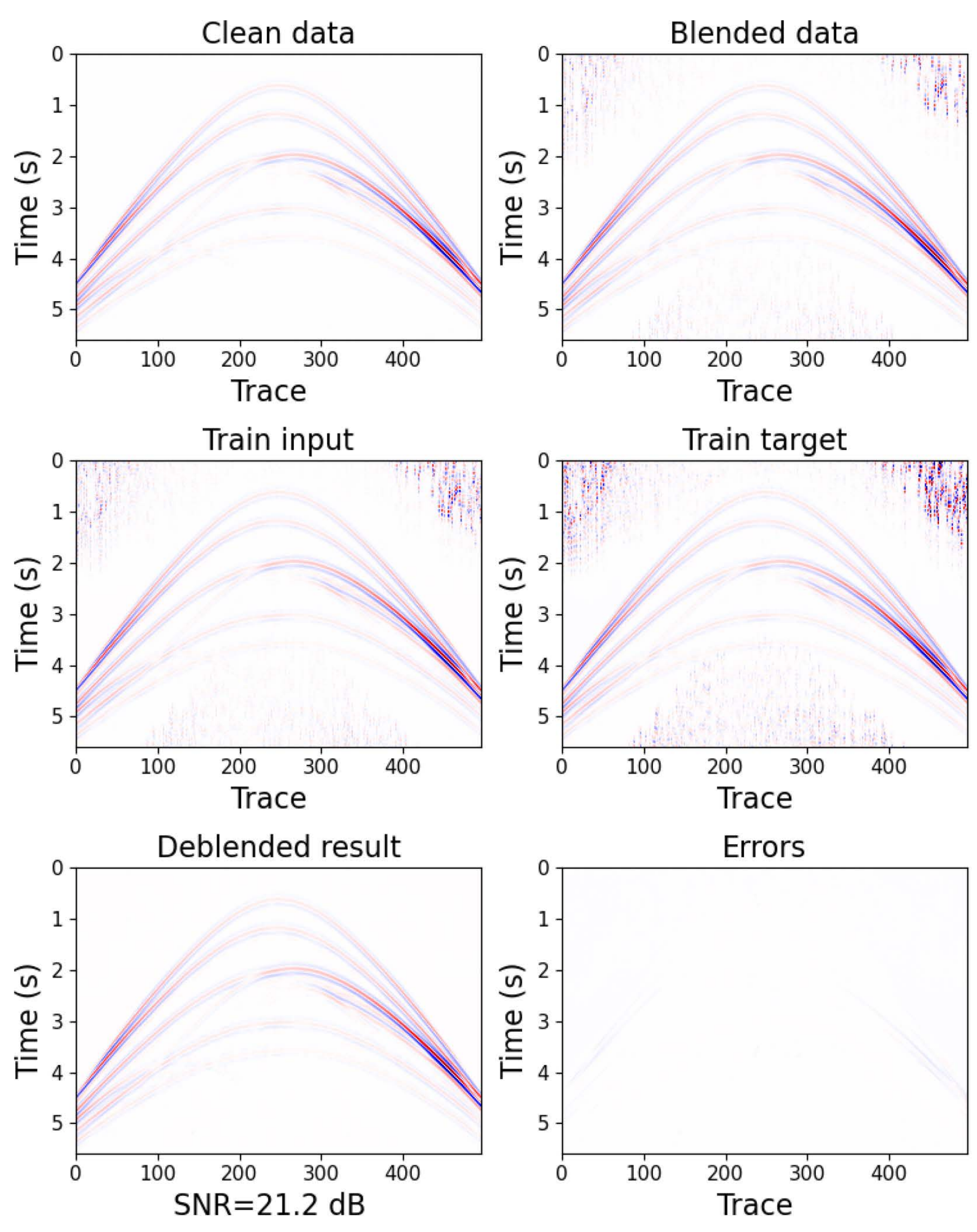

Figure 1: 2-D finite difference synthetic example.

Figure 2 shows the deblending result in common receiver gather for real marine data example.

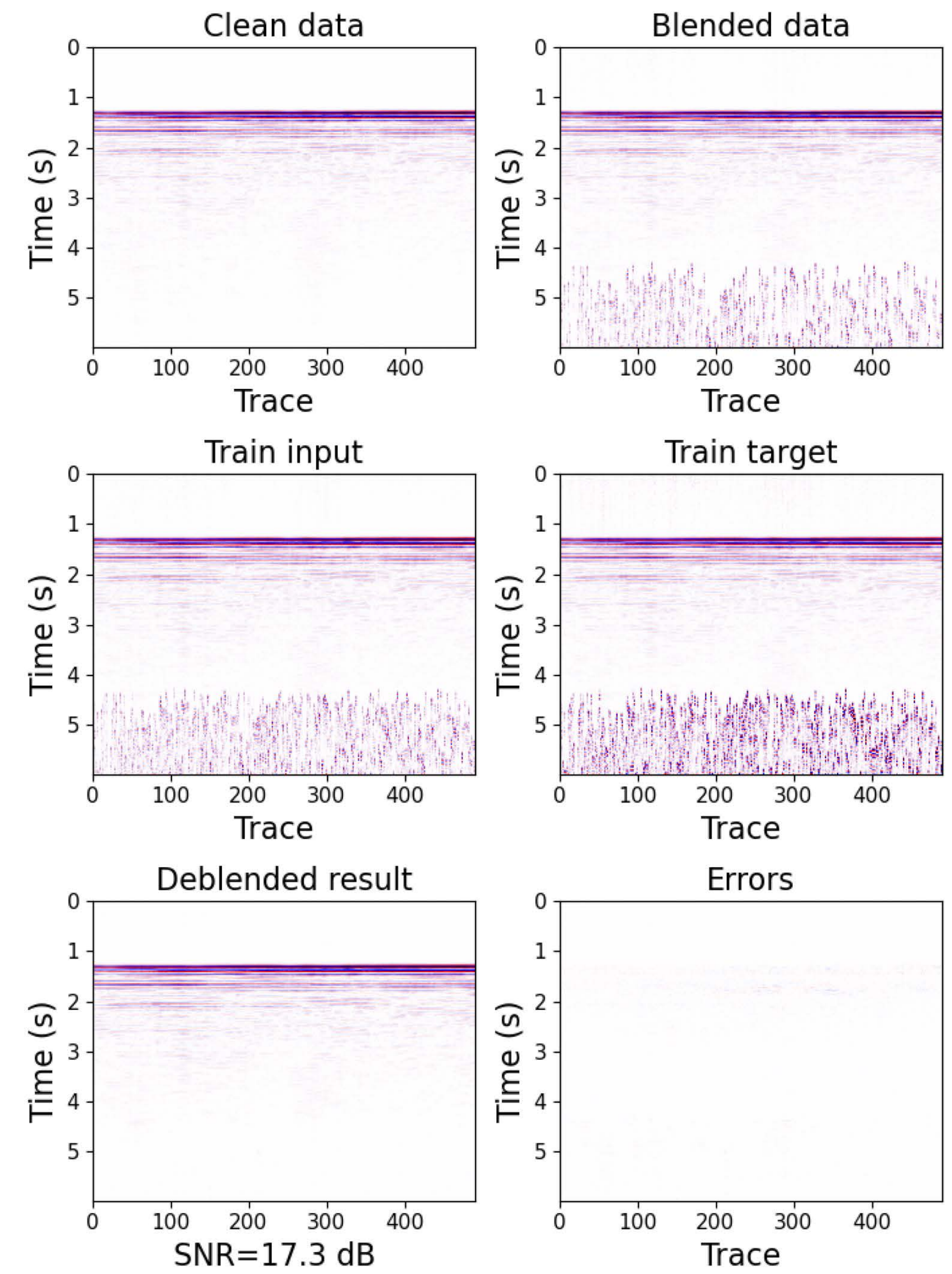

Figure 2: Common receiver gather for real marine data example.

Figure 3 shows the final deblending result in common shot gather.

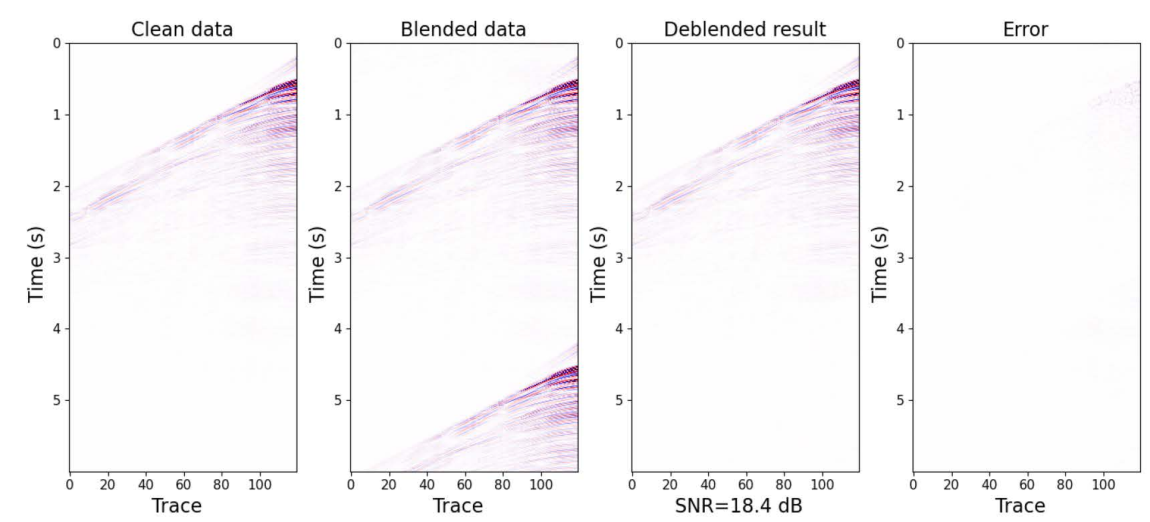

Figure 3: Common shot gather for real marine data example.

Conclusions

We introduce a novel zero-shot self-supervised framework designed to mitigate both random and erratic noise effectively. We apply our proposed framework to address the deblending challenge across synthetic and real marine data examples. It effectively eliminates blended noise without introducing significant signal leakage.

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