



Unsupervised DAS data denoising via hybrid dual channel implicit denoising network

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Summary

Distributed acoustic sensing (DAS) has gained popularity in seismic exploration due to its high coverage, resolution, sensitivity, and low cost. However, complex system layouts and harsh environments often introduce noise, reducing the signal-to-noise ratio. To address this, we propose HDCID-Net, an unsupervised dual-channel implicit denoising network. The first channel uses an ℓ_1 -norm loss to suppress erratic noise, while the second employs horizontal total variation regularization and an ℓ_2 -norm loss to model coherent noise, which is adaptively subtracted. Tested on real DAS data, HDCID-Net effectively suppresses various noise types without external training data.

Introduction

DAS technology transforms optical fibers into dense acoustic sensors, offering cost-effective, high-resolution seismic data acquisition. However, DAS data often suffer from complex noise, including erratic and coherent horizontal noise. To address this, we propose HDCID-Net, an unsupervised implicit neural network with two output channels: one reduces erratic noise, and the other models coherent noise using a hybrid loss function. The final denoised result is obtained by subtracting the modelled coherent noise from the first channel's output. Tested on field data, HDCID-Net effectively suppresses noise while preserving seismic signals.

Theory

DAS data is generally corrupted by various types of noise, including high-frequency random noise, high-amplitude erratic noise, and coherent horizontal noise (Olofsson and Martinez, 2017; Chen et al., 2018). The observed DAS data is given by

$$\mathbf{d}^{obs} = \mathbf{d} + \mathbf{n}_h + \mathbf{e} + \mathbf{n} \quad (1)$$

where $\mathbf{d}^{obs}$ is the observed noisy DAS data. $\mathbf{d}$ is the clean data, $\mathbf{n}_h$ is the coherent horizontal noise, $\mathbf{e}$ is the high-amplitude erratic noise, and $\mathbf{n}$ is the high-frequency random noise. A bandpass filter can effectively attenuate high-frequency random noise in these three types of noise. Next, we address high-amplitude erratic noise and coherent horizontal noise. By replacing the ℓ_2 norm loss function with the ℓ_1 norm loss function allows the INRs to attenuate erratic noise in seismic data. Furthermore, by incorporating the horizontal total variation regularization term into the loss function, the INRs can also be used to model coherent horizontal noise. Therefore, to remove horizontal and erratic noise from DAS data, the most straightforward approach is to use two INRs: one to model the horizontal noise and the other to attenuate the erratic noise. Afterward, we subtract the modelled horizontal noise from the noisy data to obtain the final clean result.

However, using two separate networks significantly increases the total computational cost. To address this, we propose a hybrid dual-channel implicit denoising network (HDCID-Net) that can attenuate all types of noise using a single network. First, we modify the output of the INRs. Typically, the INRs' output is the signal's amplitude at the corresponding coordinate. For our HDCID-Net, the output

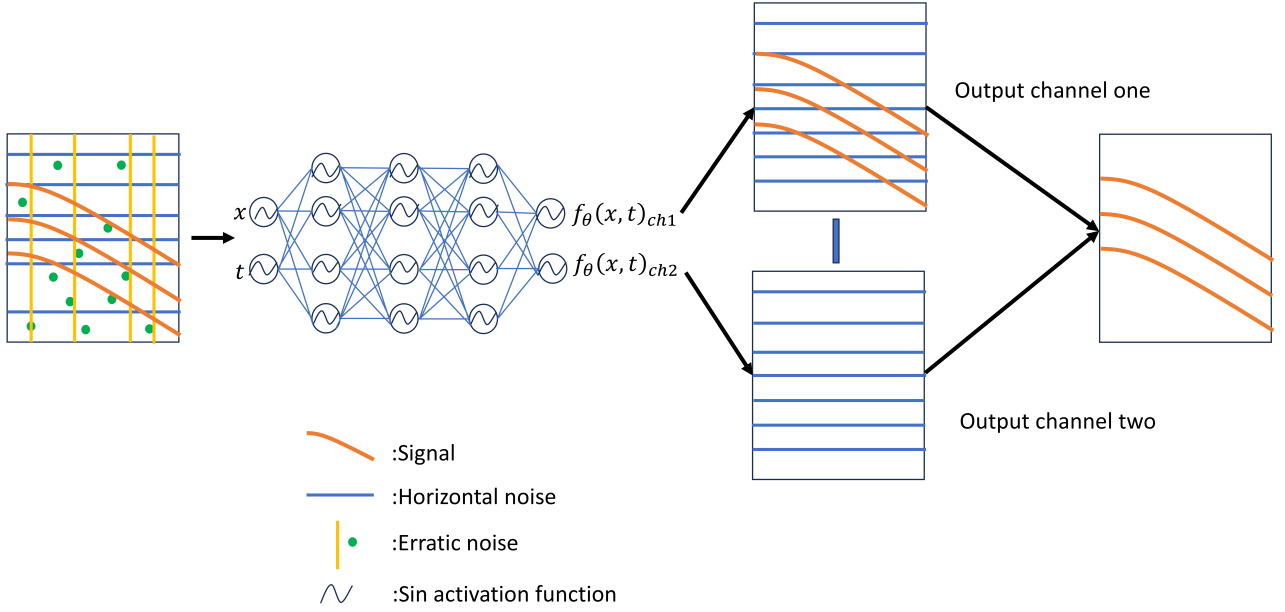


Figure 1: Illustration of the proposed hybrid dual-channel implicit denoising network.

includes two channels: $\mathbf{d}_{ch1}$ and $\mathbf{d}_{ch2}$. Here, $\mathbf{d}_{ch1}$ represents the denoised result after removing the erratic noise, and $\mathbf{d}_{ch2}$ represents the modelled coherent horizontal noise. Specifically, $\mathbf{d}_{ch1} = \mathbf{d} + \mathbf{n}_h$, and $\mathbf{d}_{ch2} = \mathbf{n}_h$, where $\mathbf{d} = \mathbf{d}_{ch1} - \mathbf{d}_{ch2}$

The loss function for the hybrid dual-channel implicit denoising network is then formulated as follows:

$$\min \|\mathbf{d}^{obs} - \mathbf{d}_{ch1}\|_1 + \lambda (\|\mathbf{d}^{obs} - \mathbf{d}_{ch2}\|_2^2 + \mu \|D_x \mathbf{d}_{ch2}\|_1) + \beta \|\mathbf{d}_{ch1} - \mathbf{d}_{ch2}\|_2^2, \quad (2)$$

where $\|\mathbf{d}^{obs} - \mathbf{d}_{ch1}\|_1$ is used to attenuate the erratic noise in output channel 1, and $\lambda (\|\mathbf{d}^{obs} - \mathbf{d}_{ch2}\|_2^2 + \mu \|D_x \mathbf{d}_{ch2}\|_1)$ is used to model the coherent horizontal noise in output channel 2. $\beta \|\mathbf{d}_{ch1} - \mathbf{d}_{ch2}\|_2^2$ can focus solely on promoting the adaptive subtraction mechanism between the two output channels. By replacing $\mathbf{d}_{ch1}$ and $\mathbf{d}_{ch2}$ with $f_{\theta}(\mathbf{c})_{ch1}$ and $f_{\theta}(\mathbf{c})_{ch2}$, respectively, the final loss function becomes:

$$\min_{\theta} \sum_{\mathbf{c} \in \mathcal{C}} \left\{ |f_{\theta}(\mathbf{c})_{ch1} - d^{obs}(\mathbf{c})| + \lambda \left((f_{\theta}(\mathbf{c})_{ch2} - d^{obs}(\mathbf{c}))^2 + \mu |D_x f_{\theta}(\mathbf{c})_{ch2}| \right) + \beta (f_{\theta}(\mathbf{c})_{ch1} - f_{\theta}(\mathbf{c})_{ch2})^2 \right\}. \quad (3)$$

Figure 1 illustrates the proposed hybrid dual-channel implicit denoising network. The network consists of an INRs with two output channels. A hybrid loss function separates the erratic noise and models the horizontal noise simultaneously. The final denoised result is obtained by subtracting the modelled horizontal noise from channel two from the denoised result in output channel one.

Example

We tested the proposed denoising network on real DAS data from the FORGE fracking program in Utah Lellouch et al. (2021). Each dataset consists of 2000×900 points, divided into overlapping patches of size 1×256 . We used the method proposed by Chen et al. (2023) on the same dataset for comparison. Figure 2a shows the noisy data example, where a bandpass filter was first applied to suppress high-frequency noise, as in Chen et al. (2023) (Figure 2b). Our method was then used

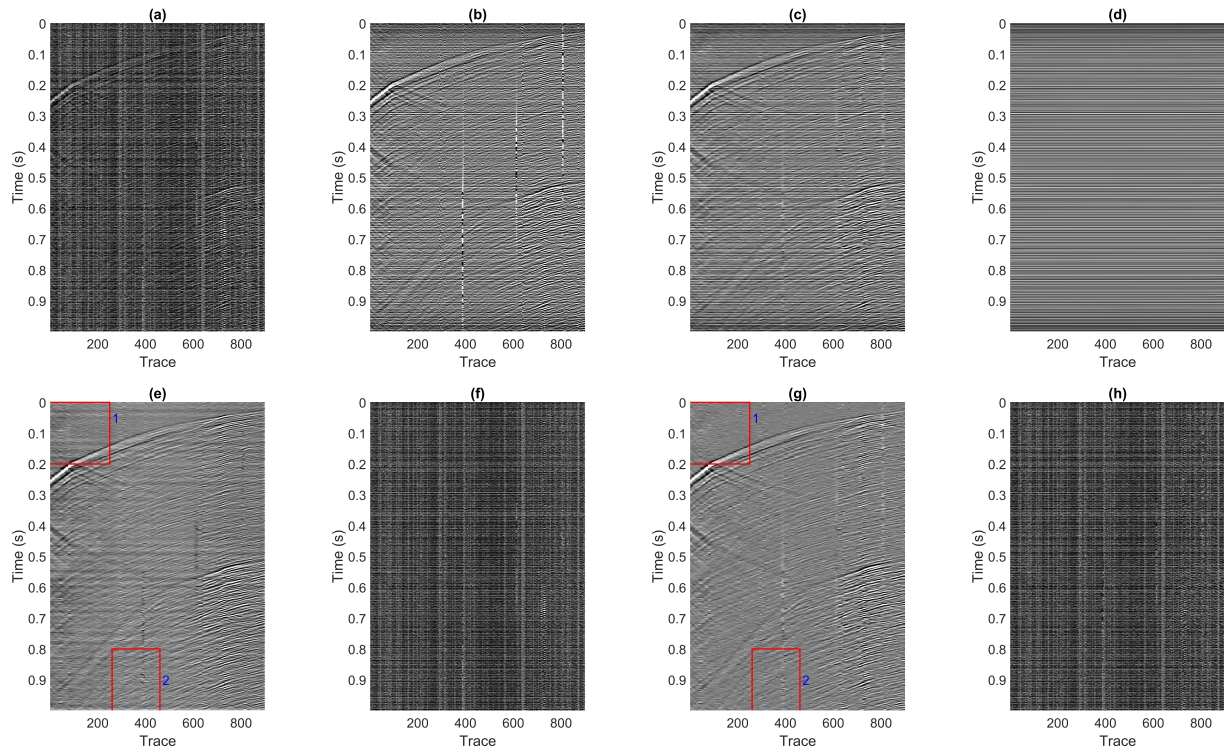


Figure 2: 2D real DAS data example. (a) Original noisy data. (b) Data after bandpass filter. (c) Denoised result from channel 1. (d) Modelled horizontal noise from channel 2. (e) Final denoised result by Chen et al. (2023). (f) Separated noise by Chen et al. (2023). (g) Final denoised result by the proposed method. (h) Separated noise by the proposed method.

to remove horizontal and erratic noise, with the final result shown in Figure 2g. In comparison, Chen et al. (2023)'s result is shown in Figure 2e. Highlighted sections reveal key differences: (1) our method removes horizontal noise that Chen et al. (2023) retains, (2) it avoids artifacts in areas of strong erratic noise.

Conclusion

In conclusion, this study proposed HDCID-Net, an unsupervised deep learning framework designed to reduce coherent horizontal and erratic noise in DAS data. By leveraging implicit neural representations with sinusoidal activations and a hybrid loss function, the dual-channel structure enables simultaneous noise modelling and attenuation while preserving key signal features. Evaluations on field datasets confirmed its effectiveness and robustness, making HDCID-Net a promising tool for enhancing DAS data quality and adaptable for broader seismic applications.

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