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Scattering Noise Attenuation Using Implicit Neural Networks in the OVT Domain

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Summary

This study develops an unsupervised method for scattering noise attenuation in the offset vector tile (OVT) domain using implicit neural representations (INRs). INRs map spatial coordinates to seismic amplitudes via multilayer perceptrons (MLPs). They inherently favour low-frequency signals due to their spectral bias. This property amplifies spatially coherent reflections while suppressing unstructured noise. The OVT domain structurally reinforces this separation. Each OVT tile focuses on one direction of subsurface structures, ensuring reflections remain aligned across tiles. Meanwhile, coherent noise in shot domains (such as ground roll and scattered noise) becomes randomized in OVTs, increasing its distinguishability to INRs. We further replace the final MLP layers of INRs with a shared 2D convolutional decoder, enabling efficient 3D correlation learning through positional encoding without explicit 3D operations. The hybrid architecture processes all OVT tiles via a single network, ensuring spatiotemporal consistency and computational efficiency. Tests confirm effective scattering noise suppression, recovery of weak deep-layer signals, and improved SNR. This framework integrates INR's continuous representation with OVT-domain physics, advancing machine learning applications in seismic processing.

Introduction

Scattering noise originates from near-surface heterogeneities in land seismic acquisition (Chiu, 2013). It poses a persistent challenge due to its spatially coherent yet irregular patterns in shot gathers. These patterns mimic reflections through spatial coherence, obscuring weak signals critical for deep reservoir imaging. Even in common midpoint (CMP) gathers, scattering noise retains velocity characteristics similar to reflections, causing overlap with useful signals. Conventional methods like frequency-wavenumber filtering and Radon filtering struggle to separate them (Bakulin et al., 2023), necessitating a processing domain that inherently distinguishes signals from noise.

The Offset Vector Tile (OVT) domain addresses this by reorganizing seismic data into azimuth- and offset-constrained subsets (Vermeer, 2001). In OVT gathers, reflections align predictably due to fixed subsurface illumination geometries. Conversely, shot-domain noise, such as ground roll, loses spatial coherence in OVT. This enhances the separability between reflections and noise. However, conventional methods process tiles individually, ignoring cross-tile correlations. High-dimensional denoising methods partially resolve this, but face prohibitive computational costs.

Deep learning approaches show promise for OVT-domain processing but face barriers. Supervised methods require labelled training data, which are often unavailable or costly to obtain for seismic datasets (Liu et al., 2022). Conventional 3D convolutional neural networks also incur high computational costs for large-scale data. Unsupervised denoising algorithms (Liu et al., 2023) eliminate the need for labels but train independently per input section, leading to inefficiency. In OVT, distinct profiles within a gather exhibit structural similarities due to shared subsurface illumination. This allows a single shared decoder to process all profiles, improving efficiency. The shared decoder also leverages cross-profile self-similarity for better denoising. However, real-world OVT data exhibits spatially correlated profile similarities that vary with position, and neglecting this prior information can lead to suboptimal results.

We integrate implicit neural representations (INRs) (Gao et al., 2024) into our framework to harness this positional prior. INRs uniquely circumvent these limitations by modelling seismic amplitudes as continuous functions of spatial coordinates through multilayer perceptrons (MLPs). This continuous representation capitalizes on INRs spectral bias, an inherent tendency to prioritize low-frequency components. Such bias aligns with reflections' coherent wavefields dominating the low-frequency spectrum. Simultaneously, scattering noise, manifesting as high-frequency deviations, fails to converge in the learned representation and is suppressed due to its lack of spatial continuity. We replace INRs final point-wise MLP layers with a shared, lightweight 2D convolutional decoder to enhance scalability without sacrificing unsupervised learning. This hybrid architecture enables unsupervised hierarchical feature extraction across OVT tiles, leveraging positional encoding to model 3D position-dependent correlations while implicitly maintaining computational efficiency. The resulting framework achieves unsupervised noise suppression by dynamically adapting denoising to the geometric context of each tile. The results demonstrate that weak deep reflections are well preserved, advancing machine learning applications in seismic processing through a domain-aware, physics-integrated approach.

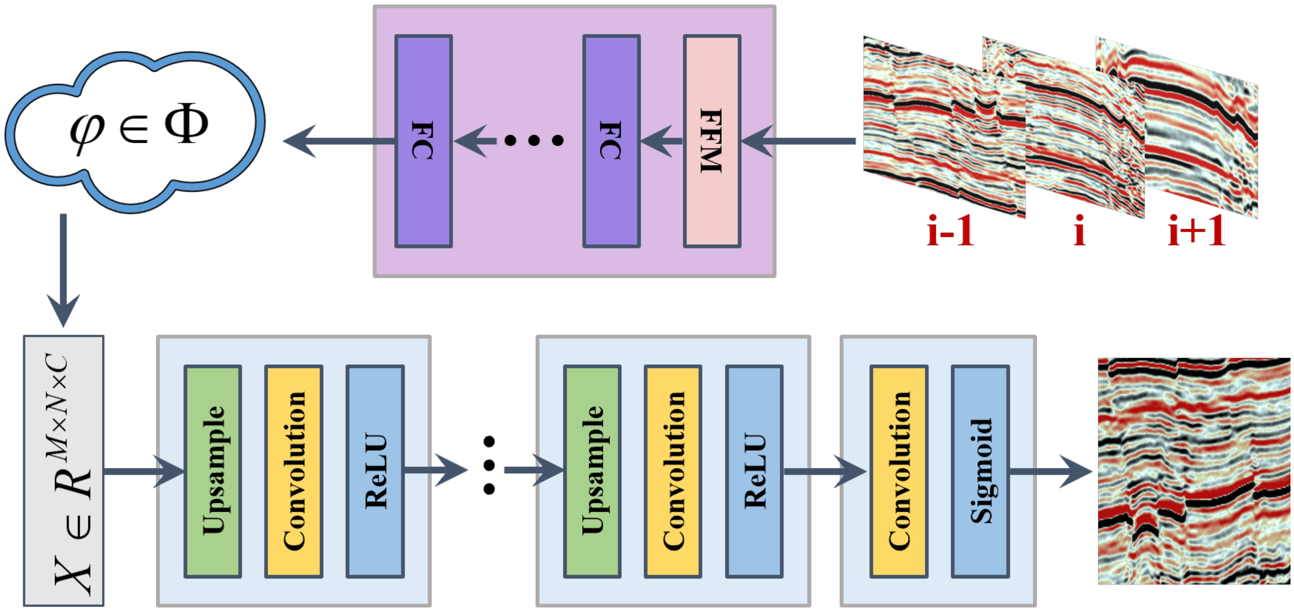

Figure 1: Network architecture for unsupervised scattering noise suppression in the OVT domain.

Methodology

Problem formulation

Let the observed OVT-domain seismic data be denoted as $\mathcal{X} \in \mathbb{R}^{N_t \times N_x \times N_y}$, where N_t, N_x, and N_y represent the time, inline, and crossline dimensions, respectively. We model $\mathcal{X}$ as:

$$\mathcal{X} = \overline{\mathcal{X}} + \epsilon, \tag{1}$$

where $\overline{\mathcal{X}}$ is the clean data and ϵ contains scattering noise and residual components. Our goal is to recover $\overline{\mathcal{X}}$ through a neural network $\mathcal{N}_\theta$ that leverages positional indices.

The network $\mathcal{N}_\theta$ maps scalar positional indices $v_i \in \mathbb{Z}^+$ to denoised sections, optimized by:

$$\min_{\theta} \sum_{i=1}^{N_y} \left\| \mathcal{N}_\theta(v_i) - \overline{\mathcal{X}}_{:,:,i} \right\|_F^2, \tag{2}$$

where $\|\cdot\|_F$ denotes the Frobenius norm.

Due to the slow variation of subsurface structures, OVT gathers exhibit strong correlations between adjacent sections due to gradual subsurface variations, while scattering noise de-correlates with offset. To exploit this prior, we introduce:

$$\min_{\theta} \sum_{i=1}^{N_y} \left\| \mathcal{N}_\theta(v_i) - \overline{\mathcal{X}}_{:,:,i} \right\|_F^2 + \alpha \sum_{r=1}^{R} \left(1 - \rho\left(\mathcal{N}_\theta(v_i), \mathcal{N}_\theta(v_{i+1})\right)\right), \tag{3}$$

where $\alpha > 0$ balances fidelity and similarity and ρ is the Pearson correlation coefficient:

$$\rho_{\mathcal{X},\mathcal{Y}} = \frac{\mathrm{Cov}(\mathcal{X},\mathcal{Y})}{\sqrt{D(\mathcal{X})}\sqrt{D(\mathcal{Y})}}. \tag{4}$$

The regularization enforces consistency between neighbouring sections while suppressing noise.

Network architecture for INR

As shown in Figure 1, we design the network architecture for representing OVTs by INRs. The architecture operates in three stages. The architecture first encodes positional indices v_i of OVT sections using Fourier feature mapping (FFM), which projects discrete coordinates into a continuous space through Fourier basis functions. These encoded features are processed by an MLP to generate latent variables φ, which are then decoded into denoised seismic sections via a lightweight 2D convolutional network. By embedding positional encoding at the input stage, the 2D decoder implicitly incorporates 3D structural relationships between adjacent sections while avoiding the computational overhead of explicit 3D operations.

Compared to 3D convolutional architectures, our 2D design achieves three key advantages: reduced computational cost during inference, fewer trainable parameters to mitigate overfitting, and inherent exploitation of global self-similarity through weight-shared convolutions. Inspired by Liu et al. (2023), we enforce low-frequency bias in the decoder through architectural constraints, critical for separating coherent reflections from scattering noise. This bias is primarily governed by the upsampling strategy in the decoder. While the PixelShuffle module (Shi et al., 2016) is common in decoder designs, its unconstrained upsampling often overfits noise. Bilinear interpolation produced smoother outputs but erased subtle features, and transposed convolutions introduced grid artifacts. In contrast, nearest-neighbour upsampling, which enforces local self-similarity, achieves an optimal balance between noise suppression and signal preservation. This aligns with the gradual spatial variations inherent to OVT-domain reflections, ensuring robust noise suppression while preserving subtle geologic features.

Results

Synthetic data results

We use synthetic data to quantitatively evaluate the denoising performance of the proposed model. First, we synthesize a clean OVT seismic dataset that includes events with controlled curvatures and time intercepts. Figure 2a shows the test mid-offset gather contaminated by real scattering noise (SNR = -5.7 dB), demonstrating our method's ability to handle realistic noise distributions. The denoised results in Figure 2b and 2c achieve 15.4 dB SNR through controlled iteration truncation, suppressing most scattering energy while preserving reflection continuity. This 21.1 dB improvement quantitatively confirms our architecture's ability to recover reflection signals from heavy noise, which is largely attributable to our positional encoding strategy and proposed hybrid architecture.

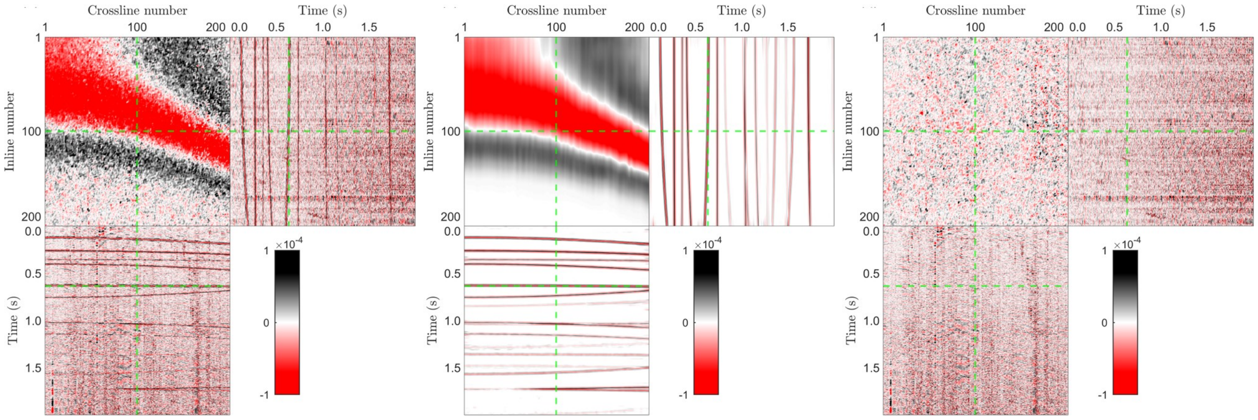

Figure 2: Synthetic data results. (a) Noisy OVT gather with added scattering noise (SNR = -5.7 dB). (b) Denoised results by our method, showing effective suppression of scattering noise while preserving coherent reflections. (c) Separated noise by our method.

Real data results

We further validate practical efficacy using 3D wide-azimuth data from a desert region with strong near-surface heterogeneity. The near-offset OVT gathers are particularly challenging due to severe near-surface scattering noise. As shown in Figure 3a, the coherent reflections are overwhelmed by strong noise, rendering many conventional methods ineffective at extracting the coherent reflection signal. Figure 3b and 3c presents the separated useful signals and the scattered noise by our method. Our approach effectively suppresses scattered noise, yielding an improved SNR. The deeper sections are significantly enhanced, confirming our methods capacity to leverage OVT-domain geometric priors for challenging geologic targets.

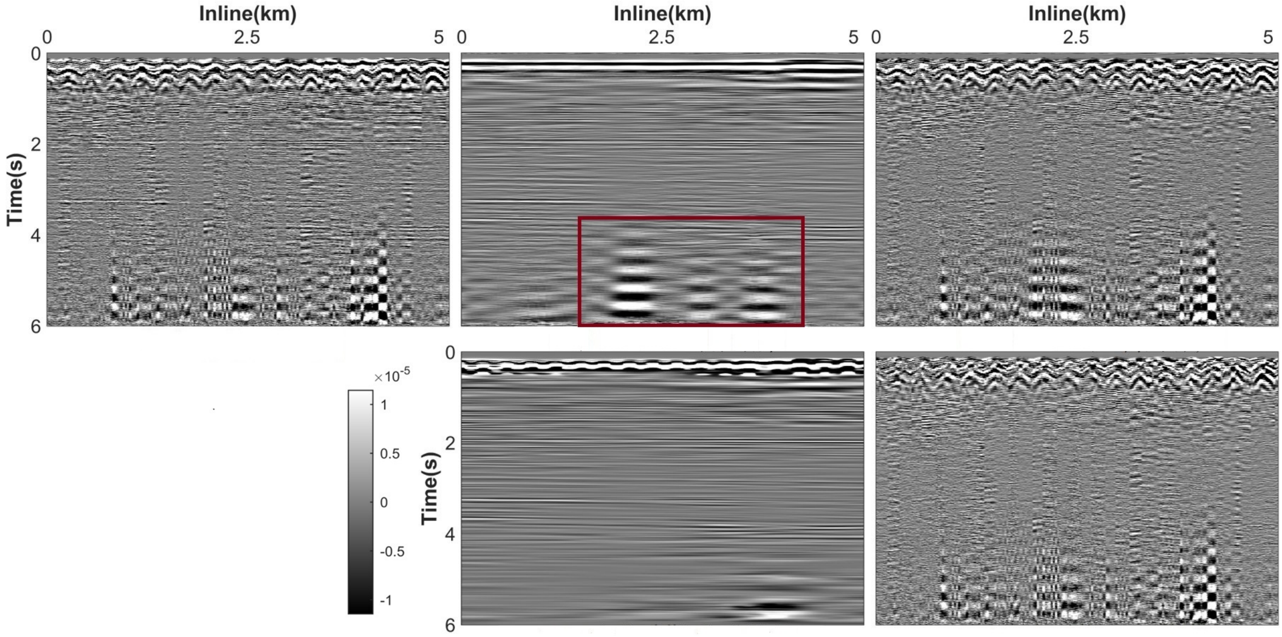

Figure 3: Real data results. (a) Raw near-offset OVT gather contaminated by strong near-surface scattering noise. (b) Denoised results by our method, highlighting recovered reflection continuity, particularly for deep events. (c) Separated noise by our method.

Conclusion

We present an unsupervised framework combining implicit neural representations with domain-aware processing for OVT-domain scattering noise suppression, bridging the gap between physical constraints and data-driven learning. By leveraging position encoding and an explicit regularization term enforcing similarity between adjacent sections, the proposed method effectively suppresses scattered noise. Quantitative synthetic tests demonstrate 21.1 dB SNR improvement, while field data applications reveal satisfactory performance in challenging desert environments, particularly for deeper sections. The encouraging results indicate that our approach provides a robust solution for enhancing seismic data quality in complex geological environments. Moreover, its label-free operation and computational efficiency make it suitable for large-scale prestack processing. Future work will refine the network architecture and extend the method to other domains.

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References

Bakulin, A., D. Neklyudov, and I. Silvestrov, 2023, Seismic time-frequency masking for suppression of seismic speckle noise: Geophysics, **88**, V371–V385.

Chiu, S. K., 2013, Coherent and random noise attenuation via multichannel singular spectrum analysis in the randomized domain: Geophysical Prospecting, **61**, 1–9.

Gao, W., D. Liu, W. Chen, M. D. Sacchi, and X. Wang, 2024, Nersi: Neural implicit representations for 5d seismic data interpolation: Geophysics, **90**, V29–V42.

Liu, D., M. D. Sacchi, X. Wang, and W. Chen, 2023, Unsupervised deep learning for ground roll and scattered noise attenuation: IEEE Transactions on Geoscience and Remote Sensing, 1–13.

Liu, D., X. Wang, X. Yang, H. Mao, M. D. Sacchi, and W. Chen, 2022, Accelerating seismic scattered noise attenuation in offset-vector tile domain: Application of deep learning: Geophysics, **87**, V505–V519.

Shi, W., J. Caballero, F. Huszár, J. Totz, A. P. Aitken, R. Bishop, D. Rueckert, and Z. Wang, 2016, Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network: Proceedings of the IEEE conference on computer vision and pattern recognition, 1874–1883.

Vermeer, G. J., 2001, Processing with offset-vector-tile gathers: 63rd EAGE Conference & Exhibition, European Association of Geoscientists & Engineers, cp–15.