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SEDGAN: A Dual Generative Adversarial Network Model for Seismic Denoising and Resolution Enhancement

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Abstract Summary

Seismic data interpretation commonly faces significant challenges due to noise contamination and inadequate resolution, leading to compromised visibility of crucial subsurface geological features. Such noise issues can lead to incorrect decisions in the oil and gas industry by obscuring essential geological details necessary for exploration and production activities. To address these challenges, this paper introduces SEDGAN (Seismic Enhancement and Denoise GAN), a sophisticated deep-learning approach leveraging advanced generative adversarial networks (GANs), specifically CycleGAN for unsupervised noise suppression and SRGAN for resolution enhancement. The model was rigorously evaluated on synthetic datasets as well as real seismic data from the Parihaka and Kerry regions in New Zealand's Taranaki Basin, representing a diverse range of geological and noise conditions. Results confirm that SEDGAN effectively suppresses both coherent and incoherent noise while significantly enhancing seismic resolution. Quantitative metrics further validate the model's capability to improve data quality without sacrificing essential geological details. Demonstrating strong generalization to previously unseen datasets, SEDGAN proves highly relevant for practical applications, substantially enhancing seismic interpretation accuracy and supporting more reliable subsurface characterization.

Introduction

Noise remains a persistent challenge in seismic data interpretation, often masking critical subsurface features and complicating geological analyses. This interference is typically categorized as incoherent—random and unstructured, common in late-arriving signals—or coherent, such as reverberations and ground roll. While conventional frequency-domain filters can reduce coherent noise, they offer limited effectiveness against incoherent components, often at the cost of signal fidelity Yilmaz et al. (2001). Recent advances in machine learning have significantly expanded the capabilities available to geoscientists, enabling effective pattern recognition, predictive modeling, and extraction of latent structures from extensive geophysical datasets Da Silveira et al. (2024); Gonçalves et al. (2024).

In this context, deep learning architectures based on Generative Adversarial Networks (GANs) Alotaibi (2020); Goodfellow et al. (2020) offer a promising alternative. Initially developed for realistic image generation, GANs have demonstrated substantial potential in geophysical applications, including data augmentation, domain adaptation, and seismic denoising Lin et al. (2023). Their ability to learn high-dimensional data distributions enables them to tackle complex noise patterns more effectively than traditional methods.

This work introduces SEDGAN (Seismic Enhancement and Denoise dual GAN), a semi-supervised framework that integrates CycleGAN for unsupervised noise attenuation Zhu et al. (2020) and SR-GAN for resolution enhancement Ledig et al. (2017). The architecture is trained on synthetic datasets with diverse fault geometries and applied to post-stack field data from the Parihaka and Kerry seismic sections in the Taranaki Basin. Synthetic exponential Gaussian noise is introduced to emulate acquisition artifacts. This framework is designed to address the dual challenge of reducing both coherent and incoherent noise while maintaining structural integrity in the seismic image, to support improved subsurface interpretation.

Theory and Methods

SEDGAN is a two-stage deep learning framework that combines CycleGAN and SRGAN to address both noise reduction and resolution enhancement in seismic data processing. The methodology operates as follows: First, CycleGAN performs unsupervised noise suppression by learning domain mappings between noisy and clean seismic images without requiring paired training data. The model uses cycle consistency loss to ensure that transformations preserve essential geological structures while removing both coherent and incoherent noise. The cycle-consistency loss is defined as: $\mathcal{L}_{cycle} = \lambda_{cycle}\mathbb{E}_{x\sim p_{data}(X)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y\sim p_{data}(Y)}[\|G(F(y)) - y\|_1]$, where G and F are generators mapping between noisy (X) and clean (Y) domains, and λ_{cycle} controls the strength of structural preservation.

Second, SRGAN enhances the resolution of denoised images from 512×512 to 1024×1024 pixels using a perceptual loss function that combines adversarial training with VGG19-based feature matching: $\mathcal{L}_{SR} = \mathcal{L}_{content} + \lambda\mathcal{L}_{adv}$, where $\mathcal{L}_{content}$ preserves high-frequency details and $\mathcal{L}_{adv}$ ensures realistic texture generation. We evaluated SEDGAN on three datasets: (1) synthetic seismic images featuring fault geometries, (2) field data from the Parihaka 3D survey (923 inlines, 1126 crosslines) in New Zealand's Taranaki Basin, and (3) Kerry field data for blind validation. To simulate realistic noise conditions, we applied exponential Gaussian noise with different levels (20%, 40%, 60%) to create training pairs.

Model performance was quantified using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and cross-correlation metrics. The framework was implemented using TensorFlow with mixed-precision training for computational efficiency. The training involved 100 epochs with Adam optimizer, employing early stopping and learning rate reduction strategies to ensure stable convergence.

Results

SEDGAN was evaluated on synthetic and field seismic datasets to assess its ability to suppress noise and enhance resolution. Figure 1 illustrates its effect on synthetic data, where key fault geometries and stratigraphic features were preserved across noise levels of 20%, 40%, and 60%. The model maintained stable PSNR values, indicating robustness under varying noise intensities.

On real field data, the model generalized well. Figure 2 shows the processed result for Parihaka inline 461, where reflectors and fault boundaries appear more continuous and interpretable. The mean cross-correlation with reference data reached 0.91, indicating strong structural alignment. In blind validation using the Kerry dataset, SEDGAN achieved 0.88, suggesting consistent performance across distinct geological settings in the Taranaki Basin.

Quantitative evaluation using PSNR, SSIM, and cross-correlation confirmed the method's ability to suppress both coherent and incoherent noise while retaining geological integrity. The slightly lower score in Kerry reflects the increased noise complexity but also highlights the model's potential in reducing migration artifacts and multiple reflections, contributing to clearer seismic sections for interpretation.

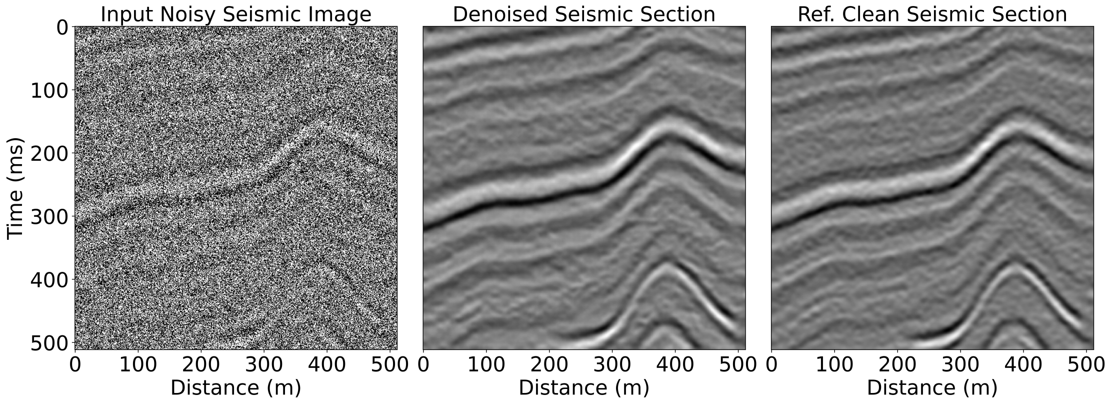

Figure 1: Denoising and enhancement of synthetic seismic data. Left: noisy input; Center: SEDGAN output; Right: clean reference. Fault structures remain identifiable after processing.

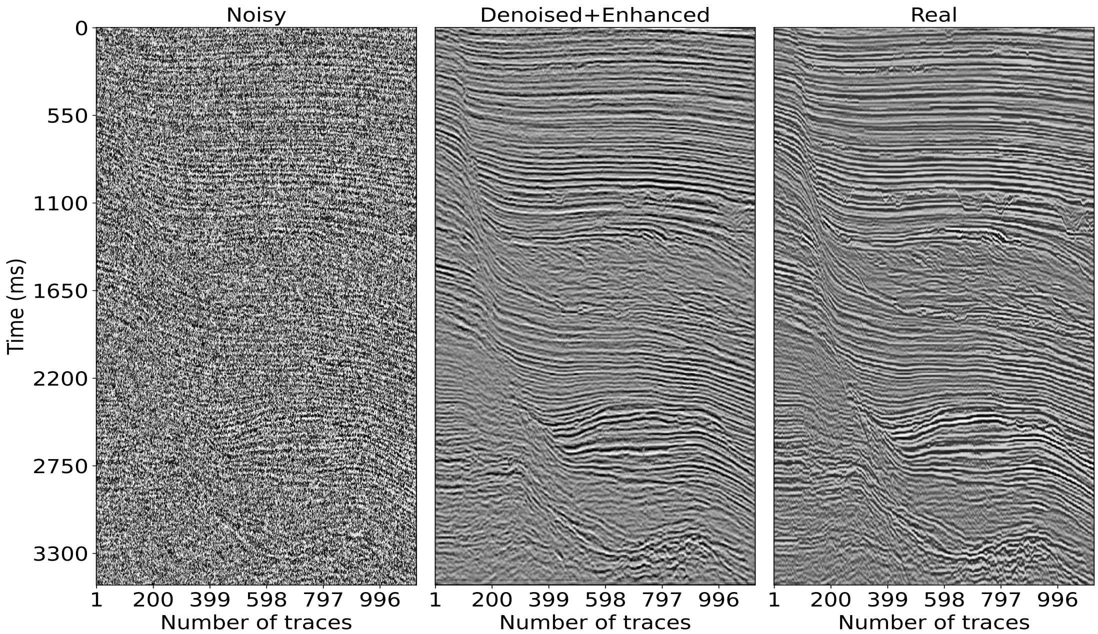

Figure 2: Processing result for Parihaka inline 461. Left: noisy input; Center: SEDGAN result; Right: clean reference. Enhanced continuity in stratigraphic features is visible.

Conclusions

SEDGAN successfully addresses the dual challenges of seismic noise reduction and resolution enhancement through the innovative combination of CycleGAN and SRGAN architectures. The framework demonstrates robust performance across synthetic and real datasets, achieving high cross-correlation values (0.91 for Parihaka, 0.88 for Kerry) while preserving essential geological features crucial for accurate subsurface interpretation.

The model's ability to generalize from training on Parihaka data to successful application on the unseen Kerry dataset highlights its practical value for operational seismic processing workflows. Beyond conventional denoising, SEDGAN enhances data quality by removing acquisition artifacts and migration noise, producing cleaner sections that facilitate improved stratigraphic correlation, fault detection, and reservoir characterization.

Future developments should focus on extending SEDGAN to full 3D volumes, implementing real-time processing capabilities, and exploring domain adaptation techniques for broader geological settings. The integration of automated hyperparameter optimization could further enhance model stability and performance consistency. These advancements will position SEDGAN as a comprehensive solution for modern seismic data processing, contributing to more reliable subsurface imaging and interpretation in exploration and production workflows.

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