Submission code: KR4V6KDAR5

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Scattering noise attenuation using U^{2}Net model on seismic data from Paraná Basin

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Abstract

This study presents a deep learning approach to attenuate coherent linear noise in seismic data from line 236-0062 at Paraná Basin. We propose the U²NetAtt to attenuate random noise. The model takes advantage of a hierarchical encoder-decoder structure with residual U-blocks (RSU) and side outputs to suppress coherent noise and preserve geological features. Evaluated on the Paraná Basin dataset, our model achieves an improvement in signal-to-noise ratio (PSNR) of 9.5% and 2.9% of SSIM. These results highlight the potential of deep learning to advance seismic data processing in complex geological environments.

Introduction

Seismic data processing in the Paraná Basin, a key sedimentary basin in Brazil, is challenged by coherent noise, such as ground roll and multiples, which obscure subsurface geological structures due to the basin's complex stratigraphy and volcanic intrusions (Yilmaz, 2001). Traditional methods, including F-X deconvolution and band-pass filtering, often fail to balance noise suppression with signal preservation (Yilmaz, 2001). Recent advances in deep learning, particularly convolutional neural networks (CNNs), have shown promise in seismic denoising by learning complex noise patterns from data (de Figueiredo *et al.*, 2013). For instance, Meng et al. (2021) successfully applied an unsupervised approach for noise attenuation. Inspired by this work, we adapted a deep learning model to process seismic data with pre-attenuated noise, leveraging bidirectional (F-K) filtering to further enhance denoising performance.

Dataset

The data set comprises SEG-Y seismic traces from Paraná Basin (line 236-0062, ANP/REATE 2021), collected in 1991. An automatic gain control (AGC) was used to improve visualization and equalize amplitude variations. Subsequently, the data was filtered in the frequency-wavenumber (F-K) domain to produce a clean data set used as labels. Initially, F-K filtering in the shot domain attenuates side-scatter noise for dips opposite to those of the reflectors, resulting in stacked data with reduced noise in one direction. Next, F-K filtering in the receiver domain, also for opposite dips, produces filtered data in both directions. This process takes advantage of the F-K domain's ability to analyze wave properties, such as velocities and propagation directions, to identify the region of interest with the highest signal concentration. The seismic data set was divided into 70% for training, 15% for validation and 15% for testing, ensuring a robust evaluation of the model. Figure 1 shows, from left to right, the noisy data, the filtered data, and a comparison of their amplitude spectra.

Method

Model Architecture

Inspired by Meng et al. (2021), we adapted the U²Net architecture for seismic noise reduction. The model employs nested structures to capture features at various scales. To increase robustness, we introduced Dropout layers with a 20% rate between hop connections, reducing overfitting. This architecture takes advantage of the lateral outputs of five hierarchical levels to refine noise reduction at different resolutions. In addition, in the jump connections, we employ simple Squeeze-and-Excitation (SE) (Hu et al., 2018) attention blocks to filter out important information that is passed on to the next level.

Training Strategy

To emphasize multiscale learning, we designed a composite loss function that combines the main output loss with an average of side output losses, encouraging the model to preserve geological features across scales. The total loss function $\mathcal{L}$ is defined as:

$$\mathcal{L} = \mathcal{L}_{\text{main}} + \mathcal{L}_{\text{side}}$$

where:

- $\mathcal{L}_{\text{side}} = \frac{1}{5}\sum_{i=1}^{5} \mathcal{L}_{d_i}$, where $\mathcal{L}_{d_i} = \text{MSE}(\hat{y}_{d_i}, y)$, $i \in \{1,2,3,4,5\}$, and $\hat{y}_{d_i}$ is the output from level d_i.
- $\mathcal{L}_{\text{main}} = \text{MSE}(\hat{y}_{\text{weighted}}, y)$, with $\hat{y}_{\text{weighted}}$ the weighted output of d_i and y the ground truth.

During backpropagation, the gradients are calculated sequentially: first for the main loss $\mathcal{L}_{\text{main}}$ and then, individually, for each auxiliary $\mathcal{L}_{\text{di}}$, with i ranging from 1 to 5.

The model was trained for 2000 epochs with a 16 batch size, on an NVIDIA GPU, using the AdamW optimizer (learning rate: 10E-4) to minimize the loss at each level.

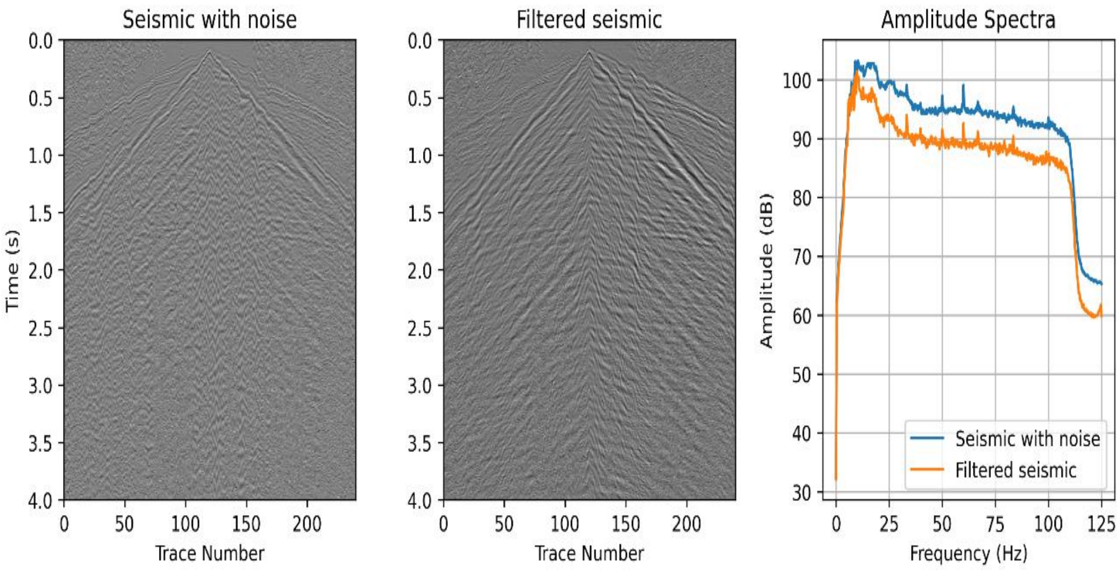

Figure 1 Comparison of a shot gather from line 236-0062, Paraná Basin: (left) noisy (original) data, (center) data filtered using bidirectional F-K filtering, (right) amplitude spectrum comparison.

Results

We evaluated the model using Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) (Wang et al., 2004), which quantify the similarity and quality of the reconstructed seismic data. To handle extreme values, seismic traces were clipped at ±8000 and normalized by their maximum absolute value, scaling data to the range [-1, 1], since standard normalization distorted the signals. Additionally, a trapezoidal filter (0–3–5–100 Hz) was applied during pre-training to attenuate low-frequency peaks, stabilizing training.

We compared the proposed model U^{2}NetAtt with a baseline Meng et al. (2021). Table 1 shows average results and standard deviations: the baseline achieved an SSIM of 42%, while our model reached 46%, a ≈ 3% gain. For PSNR, the improvement was 9.5%.

Table 1 Performance comparison of denoising models.

Model	PSNR (dB)	SSIM
Baseline (Meng et al. (2021))	22.31 ± 0.6	0.42± 0.05
U^{2}netAtt	22.9 ± 0.6	0.46 ± 0.05

Comparing the results of the model outputs reveals a consistent pattern, as illustrated in Figure 2. It can be seen that both models produce results that are visually close to the target. However, the baseline model tends to preserve the negative amplitudes of the seismic data more faithfully in relation to the target, while the proposed model excels in preserving the positive amplitudes. This difference suggests that each model may be more suitable for different aspects of seismic processing, depending on the specific characteristics of the data analyzed.

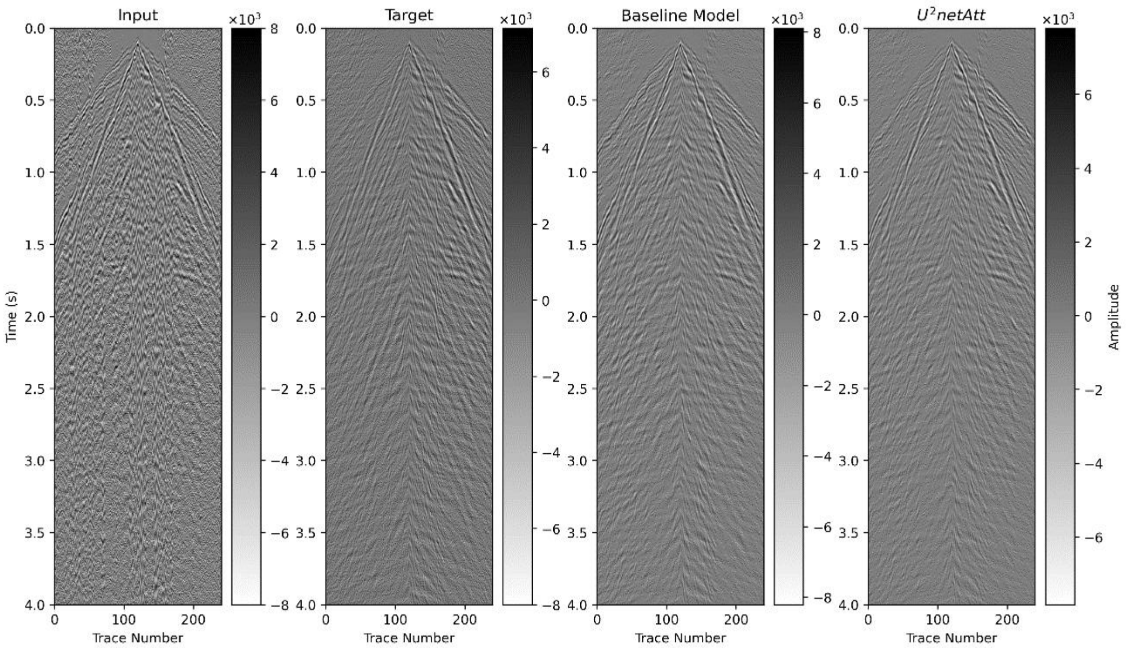

Figure 2 Example of comparison of seismic data processing results. The “Input” image represents the original data with noise, while the “Target “is the data filtered in F-K space. The “Baseline Model" image is the output of the Hu et al. (2018) model, and “U^{2}netAtt" is the output image of our model.

In addition to the visual analysis of the waveforms, the comparison of the amplitude spectra, shown in Figure 3, provides a more detailed view of the spectral performance of the models. It can be seen that the machine learning models have a spectrum closer to that of the target at intermediate frequencies, especially between 0 Hz and 40 Hz, demonstrating their ability to preserve relevant seismic information in this range.

On the other hand, the models show a smoother and more consistent spectral response at higher frequencies, which is desirable in this case, since the original data shows signal and noise convolution predominantly at low frequencies (up to around 60 Hz). This behavior highlights the complementary role of machine learning models in seismic processing, positioning them as useful tools for geophysicists in improving data quality.

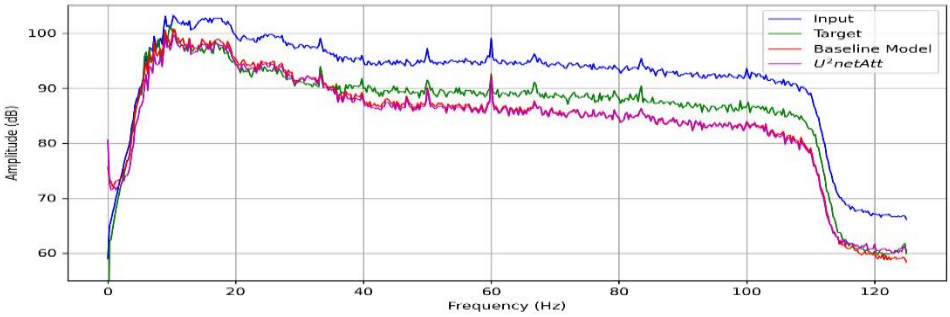

Figure 3 Frequency Spectra Comparison, indicating results are close to Target.

Conclusions

The results show that the U2netAtt model outperforms the reference approach in quantitative metrics (PSNR and SSIM), as well as showing better spectral performance in the 0-40 Hz range. A smoothing of the high frequencies was also observed, which is desirable given the predominance of noise in the low frequencies of the original data.

Acknowledgments

The authors would like to thank the Brazilian National Agency for Petroleum, Natural Gas and Biofuels (ANP) and CNPC Brasil for subsidizing this research project through the R&D Clause.

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