Submission code: 08DDRX498B

See this and other abstracts on our website: https://home.sbgf.org.br/Pages/resumos.php

Leveraging U-KAN Deep Learning Architecture for Seismic Noise Attenuation

Victor Ferreira (NCA UFMA), Alan Araújo (NCA UFMA), Luis Sepulveda (Tecgraf PUC-Rio), Carlos Rodriguez (Tecgraf Institute/PUC-Rio), Deane Roehl (Tecgraf Institute/PUC-Rio), Mauricio Almeida (NCA/UFMA), Gabriel Costa (NCA UFMA), Aristófanes Silva (NCA UFMA), Anselmo Paiva (NCA UFMA)

Leveraging U-KAN Deep Learning Architecture for Seismic Noise Attenuation

Abstract

Seismic data interpretation is often challenged by various forms of noise, which can obscure subsurface features critical to hydrocarbon exploration. This study proposes a deep learning approach based on the U-KAN architecture – an enhanced U-Net with Kolmogorov–Arnold Networks (KAN) – to perform seismic denoising on data from Paraná Basin. The preprocessing pipeline includes automatic gain control (AGC), two-stage F-K filtering, trapezoidal bandpass filtering, amplitude clipping, and normalization. The proposed model was trained using a hybrid loss function combining L1 and SSIM, and evaluated using multiple metrics. The generated images achieved an average PSNR of 25.15 dB and SSIM of 0.50, with histogram correlation of 0.9971 and spectral correlation of 0.8933. Compared to the original noisy data (PSNR = 19.09 dB, SSIM = 0.27), the results demonstrate a significant improvement in data quality.

Introduction

Seismic imaging plays an important role in hydrocarbon exploration and insights into the geological structure and composition of the Earth. However, the interpretation of seismic data is often challenged by various types of noise that can obscure subsurface features. Traditional noise attenuation methods, such as predictive filtering and sparse transform techniques, rely heavily on manual parameter tuning and expert knowledge, which can be time-consuming and may not generalize well across different datasets (Bai et al., 2019; Chen et al., 2014).

In recent years, machine learning (ML), particularly deep learning (DL), has emerged as a powerful tool for seismic data processing. DL models, such as convolutional neural networks (CNNs), have demonstrated remarkable capabilities in denoising tasks by learning complex patterns directly from the data. These models can effectively suppress both random and coherent noise without the need for explicit modeling of noise characteristics (Jun et al., 2020).

In summary, the integration of ML techniques into seismic data processing workflows holds significant potential for improving noise attenuation, reducing interpretation time, and enhancing the accuracy of subsurface imaging.

Method

The U-KAN architecture (Li et al., 2024) integrates a U-Net-inspired encoder-decoder backbone with Kolmogorov-Arnold Network (KAN) layers to improve feature extraction. Its design incorporates the qualities of U-NET, that preserves spatial information across different resolution scales, while leveraging KAN's capacity to model complex and non-linear relationships in the data, resulting in both accurate and interpretable outputs

The encoder is composed of convolutional blocks that extract hierarchical features across multiple spatial resolutions. The implementation follows the original design in Li et al. (2024).

Following feature extraction, the encoded representations are passed through the tokenized KAN stage. At this point, the feature maps are divided into 2D patches and projected into a latent space via linear transformations (Li et al., 2024). These tokenized KAN layers employ non-linear and parameterizable activation functions to model intricate patterns and boost representational capabilities.

The decoder mirrors the encoder structure, using KAN blocks and convolutional layers to progressively reconstruct the spatial resolution of the segmented image. Skip connections are used throughout the decoder to integrate high-resolution features from the encoder, which support precise denoising. The final output is a denoised seismic image.

Dataset

The data set was created with the objective of providing pre-processed and filtered seismic data, to be used as reference for noise removal analysis. The raw field data is from line 236-0062 (ANP/REATE, 2021) at Paraná Basin.

Preprocessing begins with automatic gain control (AGC) to normalize amplitude variations, followed by a double Fourier transform to convert the data into the frequency-wavenumber (F-K) domain. This allows the analysis of wave propagation properties and the identification of regions of interest. To suppress coherent noise, F-K filtering was applied sequentially in shot and receiver domains, targeting slopes opposite to those of primary reflectors to attenuate noise in both offset directions.

After F-K filtering, a trapezoidal bandpass filter with cutoff frequencies at 0, 3, 5, and 100 Hz was applied. An amplitude clipping in the [-10.000, +10.000] range was used, to mitigate influence of extreme values (outliers and spikes). As last step, the data were normalized to the [-1, 1] interval, ensuring stability and efficiency during deep learning model training.

To assert a better similarity with the filtered data, a hybrid loss function (defined in Eq. 1) was employed, combining the mean absolute error (L1) with the structural similarity index (SSIM) (Wang et al., 2004).

$$\left[\mathcal{L}_{\text{Hybrid}}(x,y) = \alpha \underbrace{\frac{1}{N}\sum_{i=1}^{N}|x_i - y_i|}_{\text{L1}} + (1-\alpha)\left(1 - \text{SSIM}(x,y)\right)\right] \quad (1)$$

Equation 1: Hybrid loss function combining L1 and SSIM.

Results

The U-KAN model was trained using a hybrid loss function on an NVIDIA RTX 4090 GPU for 400 epochs, with an early stopping patience of 60 epochs. The dataset consisted of 460 seismic seismograms in the shot domain, with 75% used for training, 15% for validation, and 10% for testing.

During the evaluation phase, the generated images were compared to the filtered targets; reconstruction quality was measured using the Peak Signal-to-Noise Ratio (PSNR) (Wang et al., 2004), SSIM, intensity histogram correlation and frequency spectrum correlation between output and target.

The average metrics and standard deviation are presented in Table 1.

	PSNR (dB)	SSIM	Hist. Corr.	Spectra Corr.
Generated Image (per image)	25.15 ± 1.35	0.5035 ± 0.0526	0.9971 ± 0.0022	0.8933 ± 0.0412
Noisy Image	19.09 ± 0.04	0.2715 ± 0.0022	—	—

Table 1: Average performance metrics on the test set.

Examples of the results are shown in Figures 1 and 2, and their amplitude spectra in Figure 3. The Target (filtered image) and the Output (model-generated image) spectra closely resemble each other across both low and high frequencies, with the output spectrum exhibiting only a slight reduction in energy. Table 1 further confirms this similarity: histogram and spectral-correlation metrics demonstrate that the generated images match the data distribution of the filtered reference.

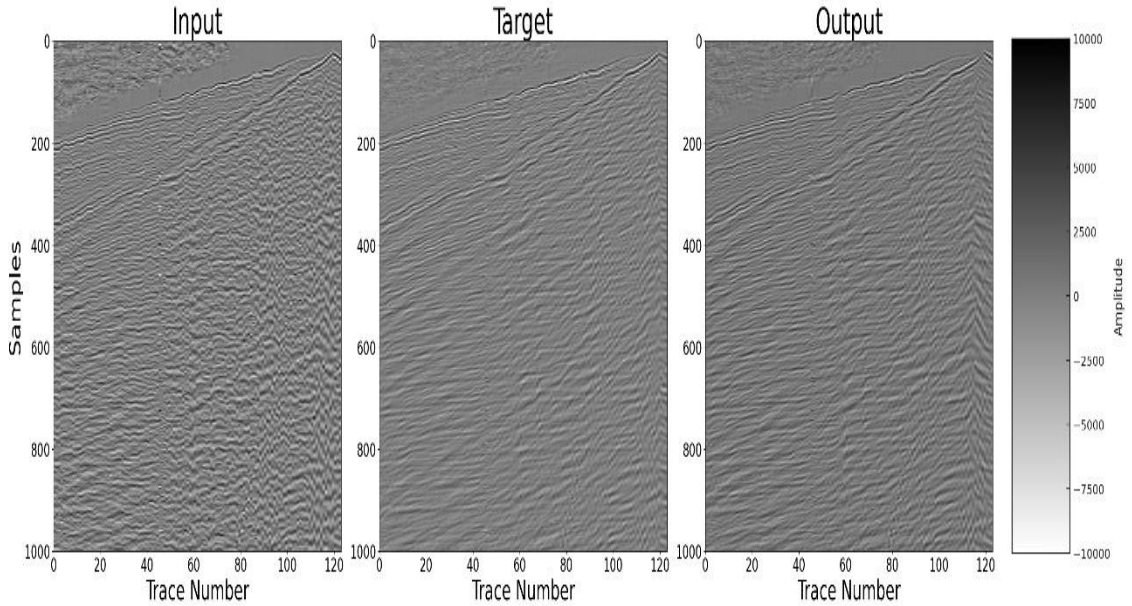

Figure 1: Input (left) is the noisy original image, Target (center) the filtered reference image, and Output (right) the network's prediction. One can see prediction results are close to Target.

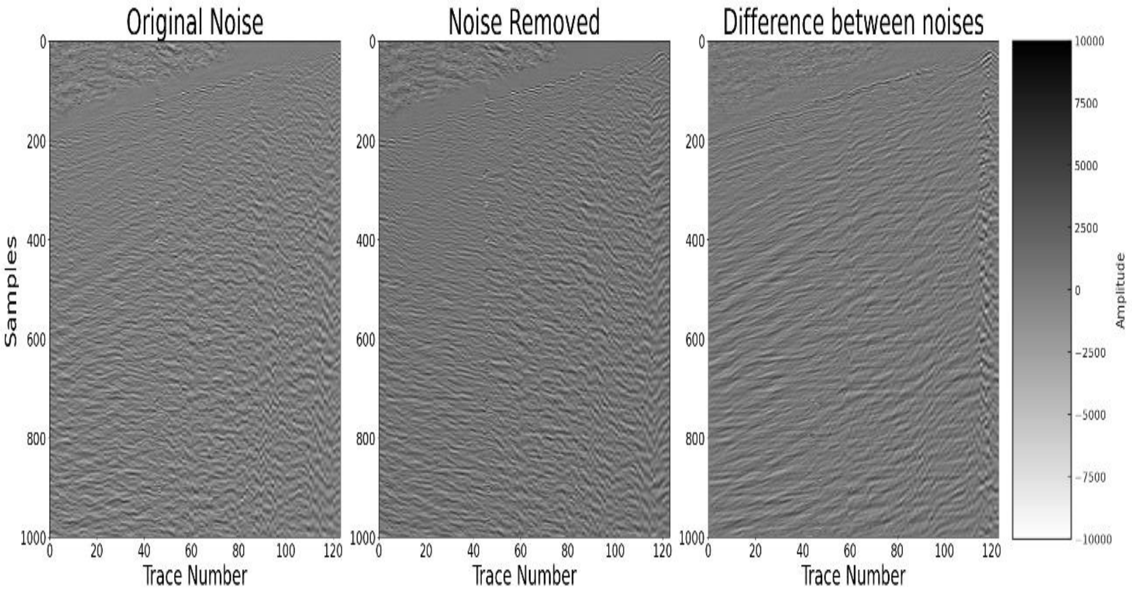

Figure 2: Original noise is the difference between Input and Target (see Fig. 1), Noise removed the difference between Input and Output (see Fig. 1), and Difference between noises is the difference between the noises present in the original data and removed by the method.

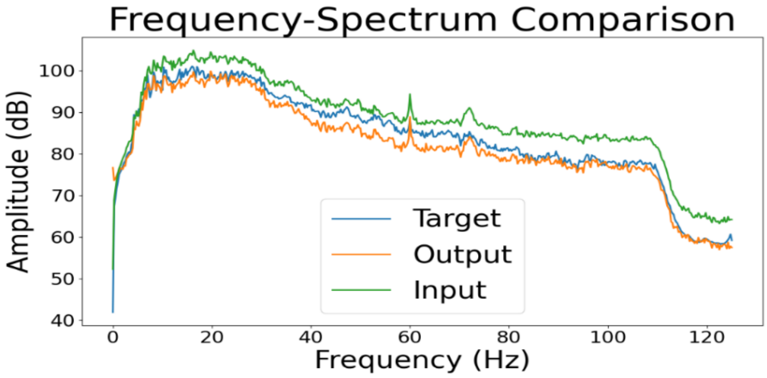

Figure 3: Comparison of the amplitude spectra, in decibels, for Input, Output, and Target (see Fig. 1). The Input exhibits higher energy levels, indicating the presence of unwanted noise. The output, generated by the model, closely follows the target spectrum.

Figures 3 and 2 also illustrate how the model attenuates noise. Whereas the Input spectrum exhibits elevated amplitudes indicative of unwanted noise, the Output spectrum preserves key signal characteristics – both amplitude levels and spectral variations – while smoothing out high-amplitude noise components. Furthermore, comparing the Original noise with the Noise removed – best visualized in the Difference between noises – reveals that traditional filtering removes more of the signal than U-KAN's output. As final conclusions, these results demonstrate that U-KAN effectively reduces noise without compromising the signal integrity of the signal.

Conclusions

The model shows promising performance, as seen in Table 1 Although the filtered reference image is not perfectly clean, Figure 2 demonstrates that the model-generated images effectively have reduced noise while preserving relevant signal. This result suggests that, by further increasing the model's receptive field, it may become capable of even better isolating noise while maintaining structural features.

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.

References

ANP/REATE, 2021, Public Land Data Free Access. https://reate.cprm.gov.br/anp/TERRESTRE

Bai, M., J. Wu, H. Zhang, M. Zhang, and Y. Chen, 2019, Gaussian beam reconstruction of seismic data: Geophysics, 84, S373–S387.

Chen, Y., S. Fomel, and J. Hu, 2014, Iterative deblending of simultaneous-source seismic data using seislet-domain shaping regularization: Geophysics, 79, V179–V189.

Jun, H., H.-T. Jou, C.-H. Kim, S. H. Lee, and H.-J. Kim, 2020, Random noise attenuation of sparker seismic oceanography data with machine learning: Ocean Science, 16, 1367–1383.

Li, C., X. Liu, W. Li, C. Wang, H. Liu, Y. Liu, Z. Chen, and Y. Yuan, 2024, U-kan makes strong backbone for medical image segmentation and generation. Wang, Z., A. Bovik, H. Sheikh, and E. Simoncelli, 2004, Image quality assessment: from error visibility to structural similarity: IEEE Transactions on Image Processing, 13, 600–612.