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Acoustic seismic inversion using a 2D convolutional neural network in the OBN seismic data of the Búzios Field pre-salt, Santos Basin, Brazil

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Abstract

We propose a CNN-based acoustic inversion using a 2D U-Net trained with perceptual loss on realistic synthetic data for characterizing pre-salt reservoirs. Our approach outperforms the conventional Bayesian linearized AVO inversion, recovering both low- and high-frequency content more accurately. Results show improved resolution and reduced dependence on the low-frequency model, demonstrating the potential of deep learning to enhance seismic interpretation in complex geological settings.

Introduction

Seismic inversion in migrated seismic data has been routinely used for pre-salt reservoir characterization in recent years (e.g., Teixeira et al., 2023). Most of the recently acquired seismic data from the Brazilian pre-salt have a broadband spectrum, obtained using ocean-bottom nodes (OBN), ocean-bottom cables (OBC), variable-depth streamers (VDS), and other acquisition technologies. The broadband characteristic, typically evidenced as a strong low-frequency content, favors the structural and stratigraphic interpretation of these deep carbonate reservoirs. However, performing seismic inversion on broadband data presents several challenges, especially in pre-salt areas, such as the need for long-duration windows from well logs and seismic data to capture low-frequency components accurately. The absence of this frequency content in the wavelet leads to an increase in inversion residuals and high instability.

Deep-learning (DL) methods revolutionized geosciences in data analysis, interpretation, and prediction. Convolutional neural networks (CNNs) are an example that manage complex geospatial data better than conventional methods and traditional machine-learning techniques. CNNs facilitate data-driven acoustic seismic inversion, eliminating assumptions in conventional approaches in forward modeling, thus efficiently solving non-linear problems. Inversion can also occur in the depth domain. However, geosciences suffer from a shortage of labeled data. Thus, an alternative approach for training the networks is to use synthetically generated datasets.

This work proposes a CNN to perform acoustic seismic inversion in the OBN post-stack data of the Búzios Field pre-salt, Santos Basin, Brazil. For that, we train a 2D CNN with the perceptual loss function in synthetic seismic data with a broadband aspect. The trained network is then applied to calculate the depth-domain acoustic impedance in the real-world field data. We analyze qualitatively and quantitatively the performance of the proposed approach, further comparing it with the maximum *a posteriori* of the Bayesian linearized AVO inversion.

Methodology

The inversion is performed in the OBN data of the Búzios Field, and the seismic image includes the application of the velocity model derived with full-waveform inversion (FWI) for the least-squares reverse-time migration (LSRTM). Our network is fully trained with synthetic data. In the following subsections, we describe the generation of this dataset for training and the network architecture.

Synthetic seismic data generation
This subsection presents the strategy adopted for generating the synthetic seismic dataset. We generated a 3D relative geological time (RGT) volume to define a structural framework featuring

a specific arrangement of faults and high-frequency folds. The RGT grid efficiently captures complex geometry, and we inserted faults and folds by following the procedure described by Wu et al. (2019). This structurally deformed RGT model was used to warp a flat-layered, geostatistics-based simulated acoustic impedance volume generated using the fast Fourier transform with moving average (FFT-MA) method.

To mimic the blurred appearance of real seismic data from pre-salt, we computed a point-spread function (PSF) using Kirchhoff operators for de-migration and migration in a homogeneous background velocity medium with random sampling following a typical distribution of pre-salt velocities. We then convolved this PSF with the reflectivity volume using a Butterworth wavelet tuned to the pre-salt broadband spectrum. As a result, we obtained four 3D volumes: RGT, faults, acoustic impedance, and PSF-convolved amplitude. An illustration of the training samples can be found at Fernandes et al. (2024).

Because our network processes 2D inputs, we randomly sampled 20 slices from each 3D synthetic seismic volume. In total, the training set comprised 10,000 seismic sections, while the test set contained 2,000 sections.

Network architecture

We dealt with the acoustic inversion as a pixel-wise regression task. To address this issue, we developed a 2D U-Net with a perceptual loss function, which consists of an auto-encoder. We opted for this strategy because perceptual loss is highly efficient for reconstructing high-frequency information in the inversion problem, thereby increasing the vertical resolution of the output (Zhang et al., 2022). This architecture takes as input a seismic section with dimensions 256×256 and outputs an acoustic impedance model with the exact dimensions. The prediction is combined with the low-frequency model and fed into the perceptual loss network, along with the acoustic impedance label, to extract features across the layers and capture high-resolution information from the data. The low-frequency model is the acoustic impedance label filtered up to 1 cycle/km; we have defined this cutoff based on the spectrum of the application data. A general network design scheme is illustrated in Figure 1.

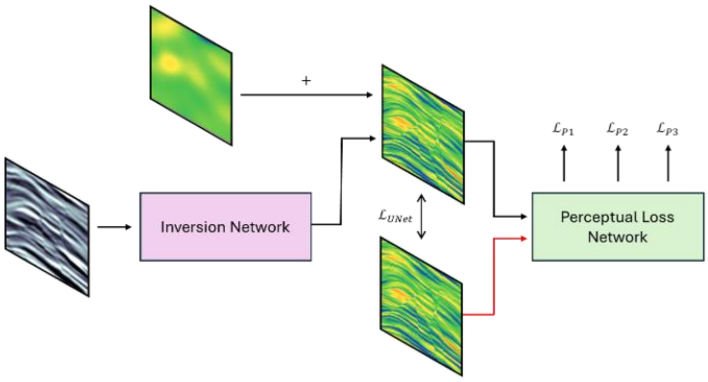

Figure 1: Scheme of the CNN for the proposed acoustic inversion.

The loss function of the deep neural network is:

$$\mathcal{L} = \mathcal{L}_{UNet} + \mu \times \sum_{i=1}^{3} \mathcal{L}_{Pi}, \quad (1)$$

where $\mathcal{L}_{UNet}$ is the loss of the inversion network, μ is the balancing factor, and $\mathcal{L}_{Pi}$ are the losses of the first three layers of the perceptual loss auto-encoder. To overcome memory issues, we employed a model-parallelization scheme in the network to split the deep-learning model across two GPUs (NVIDIA RTX A4500 with 20 gigabytes of RAM each). We trained the network for 200 epochs with a batch size of 32, a learning rate of 10^{-4}, and the Adam optimizer. The μ parameter was set to 1. U-Net parameters were ELU activations, and the number of features doubled from the first layer (64) to the bottleneck (1028). The kernel sizes of the five levels of the U-Net were 11, 11, 7, 5, and 3, respectively.

We have begun building the low-frequency model in the time domain, with 31 wells tied, and the FWI interval velocity used as an external drift for kriging the well-log data. After that, we performed the conversion to the depth domain to finally filter the model up to 1 cycle/km using a 4th-order Butterworth low-pass filter. The low-frequency model is summed with the network output multiplied by a scaling factor.

Results

Figure 2 shows the acoustic seismic inversion using the CNN in the seismic section crossing the blind test Well 1 (W1). The inverted acoustic impedance section yields a noticeably high-resolution estimate, capable of resolving thin layers that are typically challenging to delineate using conventional methods. Additionally, the inverted impedance aligns well with the well-log data, demonstrating a strong correlation between the network predictions and the ground truth. We also highlight how the network can recover the low-frequency content without artificially amplifying its amplitudes. All these factors are crucial for producing geologically realistic models that accurately represent both the large-scale structure and fine-scale variability of the subsurface, thereby improving the characterization of deep, complex reservoirs. Furthermore, our results demonstrate the importance of training deep neural networks for acoustic inversion with a dataset similar to the application data.

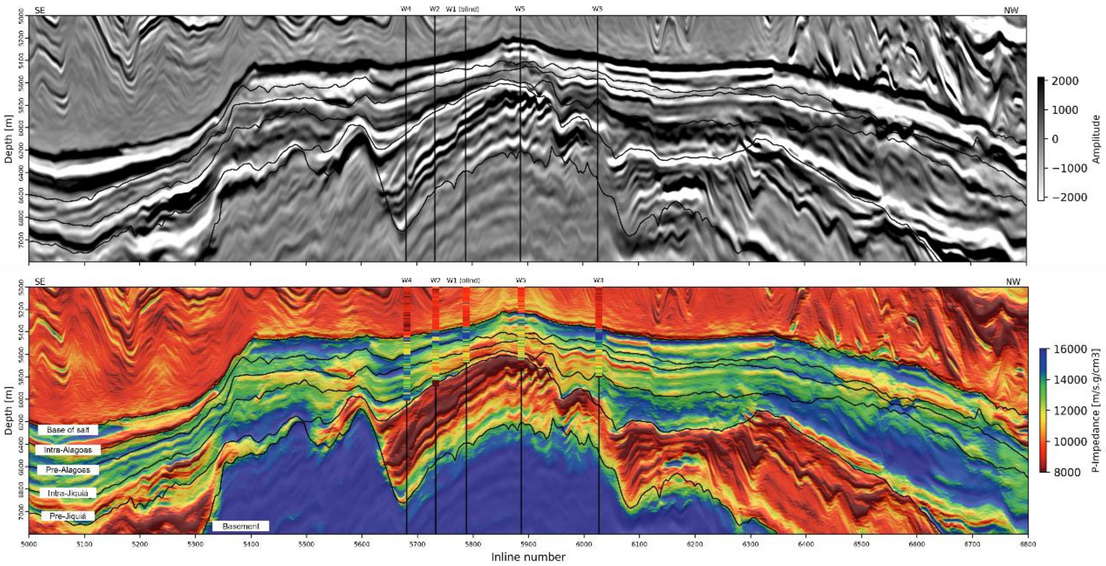

Figure 2: Acoustic inversion in the Búzios Field using a 2D CNN in the section crossing Well 1 (W1). Wells W2, W3, W4, and W5 are projected 12, 23, 3, and 7 crosslines, respectively.

Discussion

We perform a comparison of the CNN-based and the maximum *a posteriori* (MAP) of the Bayesian linearized AVO inversions (Figure 3). The MAP solution is equivalent to a Tikhonov-regularized least-squares inversion. This is the same seismic section as shown in Figure 2, but here the input data are band-limited and filtered to retain only components up to 2 cycles/km. For a medium with average velocities within the range of 2600-3100 m/s, this spatial frequency is equivalent to approximately 5-6 Hz.

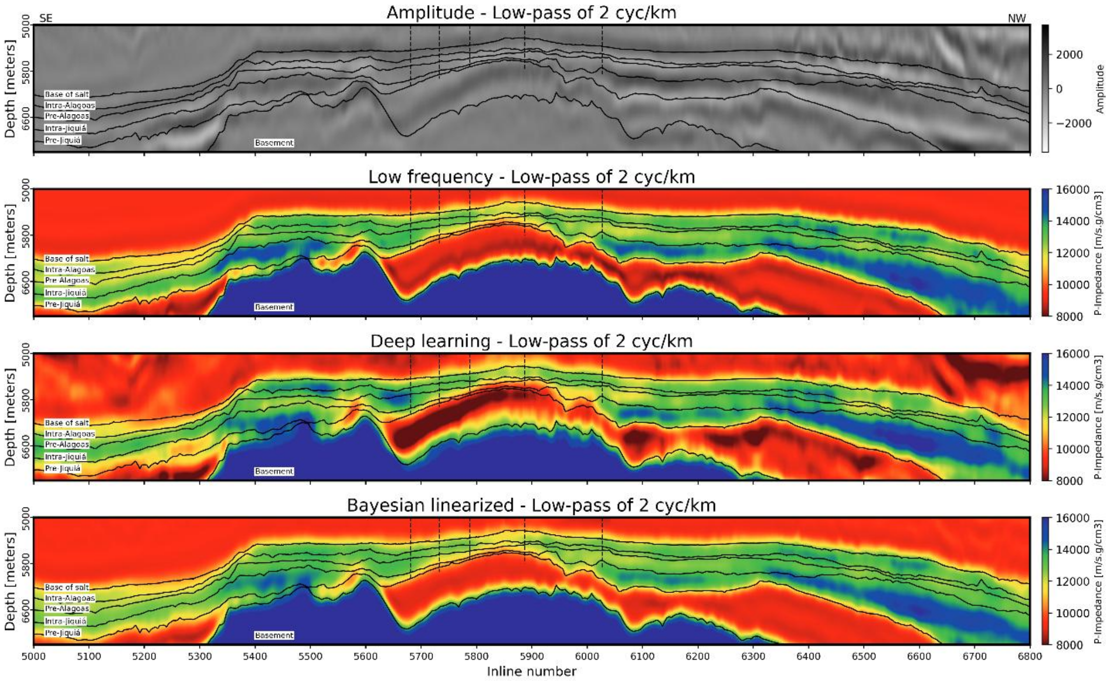

Figure 3: Comparison of both inversion approaches up to 2 cycles/km.

While the CNN-based inversion modifies the low-frequency model, reducing the bias toward the prior model, the MAP is unable to cover information in this bandwidth in the seismic, albeit low-frequency, records in the OBN data. This observation suggests that the network can extract meaningful stratigraphic and acoustic impedance variations even in the presence of limited frequency bandwidth.

Conclusions

We successfully employed a CNN for acoustic inversion in the Búzios Field, achieving a high-resolution estimate of acoustic impedance. The result shows how crucial training networks are for acoustic inversion using a dataset that closely resembles real-world application data. The fact that the CNN result diverges more from the low-frequency prior indicates that the network is not merely replicating the low-frequency trend but instead learning to exploit subtle amplitude variations in the low-frequency range to reconstruct high-resolution impedance models.

Acknowledgments

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References

Fernandes, F. J. D., Neto, E. R. O., Teixeira, L., and Lupinacci, W. M., 2024, Impact of the Seismic Forward Modeling Method on the Deep Learning-Based Impedance Inversion in Brazilian Pre-Salt. In: *Third EAGE Conference on Seismic Inversion* (Vol. 2024, No. 1, pp. 1-5). EAGE.

Teixeira et al., 2023, Rock-physics-assisted interpretation of elastic property of the geological environments in the Buzios Field, Brazilian pre-salt. In: *18th International Congress of the Brazilian Geophysical Society*, Rio de Janeiro, RJ, Brazil. SBGf.

Wu, X., Liang, L., Shi, Y., and Fomel, S., 2019, FaultSeg3D: Using synthetic data sets to train an end-to-end convolutional neural network for 3D seismic fault segmentation. *Geophysics*, *84*(3), IM35-IM45.

Zhang, S. B., Si, H. J., Wu, X. M., and Yan, S. S., 2022, A comparison of deep learning methods for seismic impedance inversion. *Petroleum Science*, *19*(3), 1019-1030.