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Depth-domain 4D Seismic Inversion Using Convolutional Neural Networks (CNNs)

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Abstract Summary

This study investigates the use of Convolutional Neural Networks (CNNs) to address 4D seismic inversion problems for predicting reservoir properties in the depth domain, using the UNISIM dataset. CNNs were selected for their ability to capture complex non-linear relationships between input and output data. The model was applied to variations in four properties between the base and monitor seismic cubes: ΔV_p, ΔV_s, delta density ($\Delta\rho$), and delta water saturation (ΔS_w), as well as base porosity (ϕ) to support additional inversions. A separate network was trained for each property using a standardized trace-by-trace approach. Performance was evaluated using the root mean square error (RMSE) calculated over the entire inverted volume and assessed for petrophysical consistency. The inversion demonstrated a strong capability to estimate property variations. Additionally, we observed that different network architecture configurations significantly affect result quality, suggesting that exploring alternative machine learning models could further enhance the method.

Introduction

Traditional seismic inversion workflows are typically conducted in the time domain using the convolutional model. However, 4D seismic inversion aims to estimate temporal changes in reservoir properties such as saturation, and pressure (Lumley, 2001). These physical properties are inherently functions of depth rather than time, which creates a conceptual misalignment when using time-domain inversions (Cai et al., 2022).

In the time domain, 4D effects — particularly changes in seismic velocity between surveys — alter signal arrival times, potentially causing the apparent movement of reflectors and misleading the inversion process. Conversely, in the depth domain, these velocity variations are incorporated into the time-to-depth conversion model, reducing artifacts and enhancing interpretability (White and Simm, 2003).

Operating in the depth domain offers several advantages. Depth-aligned estimates are more directly comparable to geological models and simulation outputs. The availability of detailed and iteratively updated velocity models, combined with advanced migration techniques like Pre-Stack Depth Migration (PSDM) and Full Waveform Inversion (FWI), allows for accurate and stable conversion of seismic data into the depth domain (Calvert, 2005). Moreover, Depth-domain inversion enables direct comparison and integration with reservoir simulation, which is essential for integrated 4D workflows combining production history and seismic data.

Convolutional Neural Networks (CNNs) provide significant benefits for this type of inversion by framing it as an image recognition task. CNNs excel at learning complex and nonlinear spatial relationships between seismic depth images and rock properties such as velocity, without requiring an explicit initial model or a perfectly defined wavelet, and have been used in many recent studies to perform inversions (Das et al., 2019; Mosser et al., 2018; Wu et al., 2019).

In this work, we propose a method using CNNs to directly estimate property changes (Δ) between base and monitor seismic cubes in depth, based on amplitude differences from the depth-converted surveys. This approach enables more reliable reservoir monitoring (Johnston, 2013), and we validate its robustness using the UNISIM synthetic model, an established industry benchmark (Avansi and Schiozer, 2016).

Method and/or Theory

4D seismics have been growing in prominence in reservoir engineering in recent years. A 4D seismic is, in essence, a stack of surveys taken in different times over the course of oil extraction in a given area. By 4D inversion, then, we mean the estimation of the change in reservoir properties over the years. This enables the engineer to model the flow of fluids in every region of the reservoir, even those that were not sampled (Lumley, 2001).

There have been many recent studies that propose different methods for depth-domain inversion. In a paper from 2022 (Cai et al., 2022), Cai et al. proposed an iterative method that combines the multiple time-depth conversions into one, mitigating losses. In another paper, from 2019, (Waters et al., 2019) Waters et al. use a machine learning method to perform facies inversion in depth domain. Likewise, we sought to use deep-learning networks to perform the 4D inversion process, and model the flow of oil water in the reservoir.

In terms of which machine learning method was chosen, the most fitting one were Convolutional Neural Networks (CNNs). There is precedent displaying the power of CNNs for seismic inversion. Li et al. (Li et al., 2022) explore multiple different architectures of CNNs with the goal of determining which are more adequate for seismic modeling. A separate study by Liu et al. (Liu et al., 2024) investigates an architecture that combines CNNs with Genetic Algorithms to achieve seismic inversion. CNNs excel at image recognition, and as such are useful in order to distinguish the features that compose each trace.

Additionally, Zhu et al. (2022) Zhu et al. (2022) introduced a multi-scale strategy for data-driven seismic inversion, where seismic data at different frequency scales are processed to help the network learn high-frequency features, demonstrating the sensitivity and importance of the input data representation for the CNN's performance.

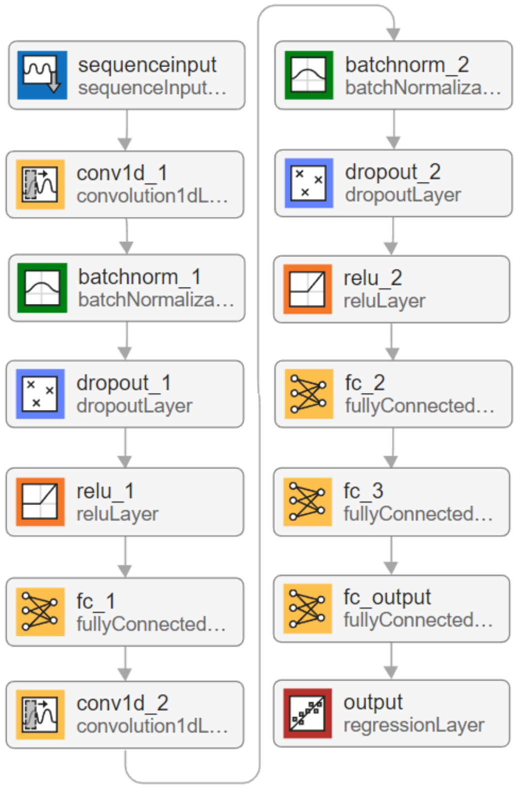

Figure 1: Architecture diagram for the Convolutional Neural Network (CNN) used in this study.

For our study, the CNN was built using a common structure for each inversion, altering only the number of channels and output sized based on the data and target property. The architecture (Figure 1) starts with a sequence input layer (`sequenceInput`), followed by a convolutional 1d layer (`conv1d`) with 30 filters of size 30. After it, we placed a batch normalization layer (`batchnorm`), a dropout layer (`dropout`) and a ReLu (`relu`) layer as the activation function. This block is closed by a fully connected layer (`fc`) with size 48, before it is repeated and closed with a fully connected layer of size 24. The architecture ends with two other fully connected layers, one of size 12 and the other with size equal to the number of outputs, and concluding with a regression layer.

Our network was trained over 80 epochs with an initial learning rate of 0.001. For each inversion, we took 378 non-zero traces selected from the data with equal spacing between them. From this set, we randomly selected 80% for training and 10% for validation, discarding the other 10%.

Experiments and Results

During this study, we took from the UNISIM reservoir a few key properties for seismic modeling (Bosch et al., 2010): V_p, V_s, density (ρ), porosity (ϕ), water saturation (S_w) and four seismics taken at different angles (Near, Mid, Far and Ultra-Far) in time and converted them to depth. We then calculated the variation in those properties between the base and monitor datasets, resulting in the cubes ΔV_p, ΔV_s, $\Delta\rho$, and ΔS_w. Since the porosity is assumed to stay constant, there is no need to take its variation over time. For each of those properties, we performed the inversion using the networks described above, choosing inputs that reflect the necessary properties for a traditional inversion. After the networks were trained, we predicted every other trace not in the training set from the reservoir to produce a compound cube, then took the RMSE from the compiled cube. The results are presented as a horizontal slice at $y = 150$ to ease visualization.

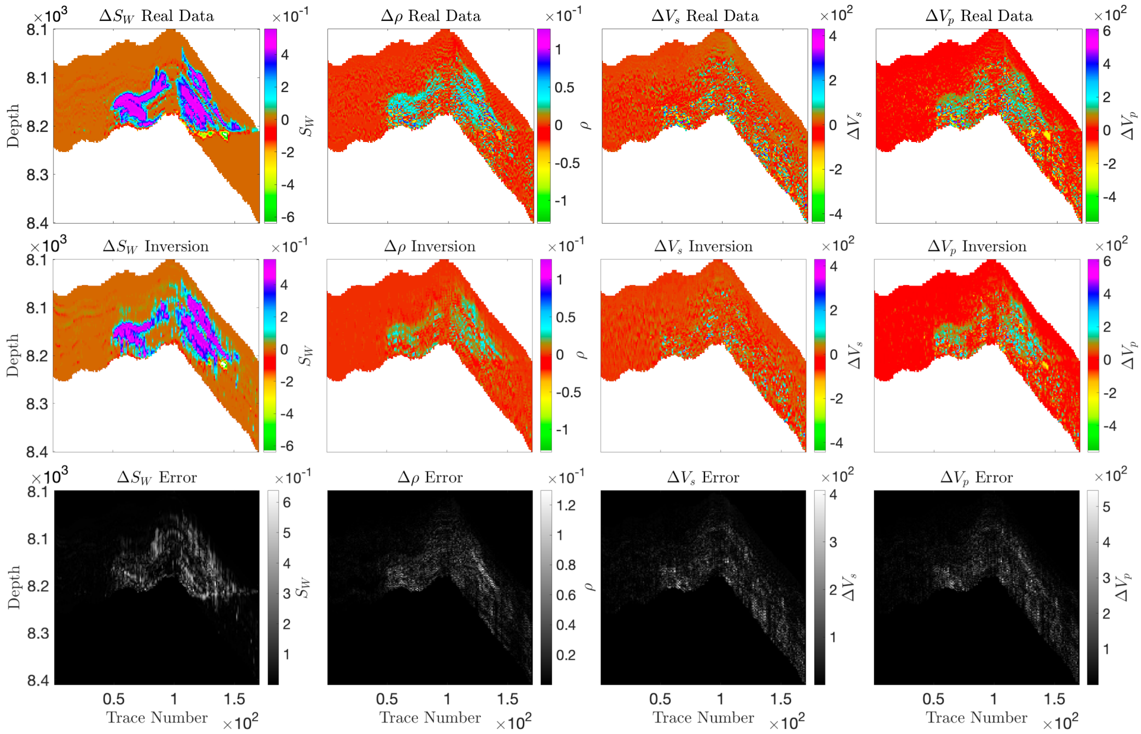

Figure 2: The four inversions performed for this study. The top four images represent the real data, the middle ones are the results our model achieved, and the ones at the bottom are the absolute error for each of them.

We used a single network with two channels to invert to both ΔV_p and ΔV_s, performing both inversions at the same time. For this inversion, the four seismic cubes were used as inputs, with the target properties set as outputs.

Density is typically a difficult property to perform inversions to. We used the Δ seismic as inputs and $\Delta\rho$ as the output. Our inversion showed some artifacts of the machine learning process, not completely reflecting the change in density of the reservoir. Despite this, it highlights the area where extraction would have been performed. The regions with positive change in density are where the oil was expelled by the water, increasing the overall density of the rock. This is better seen in the inversion to ΔS_w. The inputs for this inversion were the same seismic as before, plus porosity, $\Delta V_p/\Delta V_s$, and ΔI_p and the output was ΔS_w. To perform a more realistic test, the inputs used were the results of previous inversions (besides the seismic). As with ρ, we expect S_w to increase in the regions where extraction was performed, and they do correlate very closely as seen in Figure 2.

Table 1: Root Mean Square Error (RMSE) for the inverted properties

Prop.	RMSE	Prop.	RMSE	Prop.	RMSE	Prop.	RMSE
ΔV_p	66.1786	ΔV_s	52.9278	$\Delta\rho$	0.0147	ΔS_w	0.0876

The performance of the inversions was quantitatively evaluated through the calculation of the RMSE. This error was computed for each inverted property, confined to the reservoir area defined by a specific mask. The RMSE is a standard metric used to quantify the discrepancy between predicted and observed values in regression problems (Chai and Draxler, 2014). The RMSE of the five 4D inversions are displayed in Table 1.

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Conclusions

With this study, we have demonstrated the application of Convolutional Neural Networks for 4D seismic inversion in the depth domain using data from the synthetic UNISIM cubes. The capability of CNNs in seismic inversion tasks has been corroborated by several recent studies. The visual presentation of the results and the quantitative analysis via RMSE indicate the CNN's ability to learn complex mappings between seismic data and subsurface properties. As shown, the technique has room for improvement and investigation, and incites further exploration of other machine learning methods that could be applied to solving inversion problems in which convolutional approaches struggle with.

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