Automated fracture-zone prediction in multi-azimuth seismic data using deep learning

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Abstract

The identification of natural fractures is a critical task for defining production development projects and managing hydrocarbon-bearing reservoirs. However, it is a complex activity due to the involvement of data acquired at multiple scales and observation supports. A methodology was developed for the automated recognition of fractured zones in seismic data with Full Azimuth using Machine Learning techniques, where the training labels are obtained from the interpretation of fractures in image logs. The limited amount of available training data necessitated the use of two distinct strategies: (i) data augmentation techniques and (ii) network feedback with predictions near the training wells. Initial results showed that the proposed methodology is promising requiring further improvements.

Introduction

Reservoir characterization is a crucial step in forecasting oil production. The positioning of geological heterogeneities (e.g., faults, fractures, vugs, karsts) directly influences reservoir dynamics and can lead to the early breakthrough of water and gas in producing wells. Interpreting these heterogeneities, which are often found in the pre-salt carbonate reservoirs, is of utmost importance for the development of these oil fields.

Seismic data analysis and interpretation allow for the identification of geological structures; however, it is a challenging task when it comes to fractures that are at the resolution limit of seismic data. In this context, the wealth of information provided by pre-stack data with full azimuth is fundamentally important, as the literature reports a relationship between amplitude variation vs. offset and azimuth in the presence of fractured zones (Fang et al., 2017; Hall and Kendall, 2003). This variation indicates anisotropy (Harwood et al., 1998), which may be caused by fractured rocks in the region (Clark et al., 2009).

Several machine learning approaches have recently been reported for applications in seismic data analysis and interpretation, mainly using computer vision models via convolutional networks (Zheng et al., 2019; Wang et al., 2020; Cheng et al., 2023; Sheng et al., 2023). Significant advancements have been observed in fault identification, producing methods applicable to different contexts (Wu et al., 2019). Identifying fractures from seismic amplitudes has also attracted the interest of various authors, who frequently apply machine learning techniques for this purpose (Cheng et al., 2022; Babasafari et al., 2022; Yuan et al., 2021). However, the use of pre-stack data with azimuthal richness in conjunction with deep learning techniques can still be further explored for this task.

The objective of this work is to develop a methodology for identifying fractures from pre-stack seismic data with azimuthal richness. The labels for each training example are based on processed information from P32 fracture density logs. These logs refer to volumetric fracture density, indicating the area of fractures per unit volume of rock (Dershowitz & Herda, 1992), and are the product of the interpretation of well image logs carried out by the Production Asset team of a pre-salt field. The proposal is to use neural networks to map the presence of fractures as a function of the azimuthal distribution of seismic amplitudes. However, the amount of data extracted from these logs does not allow for the creation of very complex networks. To overcome this limitation, two additional strategies are proposed: data augmentation and feedback. Data augmentation generates new training examples from transformations of the original data using computer vision techniques adapted to the context of this work to avoid generating spurious data. Feedback allows data extracted from the network's predictions to be included in the training of new networks. However, a validation process is necessary to ensure the reliability of this data to prevent network degeneration, using only those that are highly likely to be correct. To test the feasibility of the methodology, data from a producing field in the pre-salt of the Santos Basin were used.

Method

The approach to inferring geological heterogeneities, such as fractures and faults, using convolutional networks with seismic data has recently shown significant results (e.g., Wu et al., 2019; Yuan et al., 2021). This work proposes to follow this line by applying multichannel convolutional neural networks for binary classification of seismic points based on a pre-stack data volume with azimuthal richness surrounding them. Each channel corresponds to an azimuth-offset pair of information. To provide the labels needed for training, a well-log-based annotation process is employed, detailed below. It is known that this annotation

process generates relatively few training data, allowing only very simplified network architectures. To address this issue, two additional steps are proposed: data augmentation and network feedback, enabling predictions to be incorporated as training data to allow for more complex architectures.

Figure 1 illustrates the workflow, divided into three stages: data labeling, data augmentation, and supervised learning.

The first stage, called data labeling, encompasses the entire processing of raw data: identifying fractures from the P32 profiles of each well, matching these data with seismic resolution, and extracting the seismic amplitudes corresponding to the points where the well data were annotated. This stage also allows for flexible process configuration, facilitating comparative analyses. These configurations include different processing methods, such as upscaling techniques and filtering procedures for the well-log data. Notably, there is the possibility to select different cutoff frequencies for the low-pass filter applied to the well log data. The lowest frequency capable of covering a user-defined percentage of the frequency spectrum is selected. The effect of this percentage will be analyzed in more detail in the following sections.

The second stage is data augmentation, aimed at expanding the training set. Only transformations that do not corrupt the geophysical characteristics of the extracted seismic data were selected: 90°, 180°, and 270° rotations in the horizontal plane; horizontal flips; and brightness adjustments by multiplying the amplitudes by a constant factor.

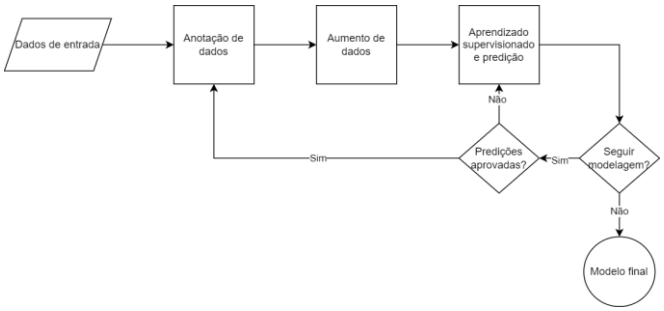

Figure 1 - Flowchart of the adopted methodology.

Finally, the third stage is the supervised learning phase, which includes preprocessing, with regularization of the azimuth/offset angle distribution and normalization; the definition of network architecture and other training configurations (number of epochs, loss function, etc.); the actual network training; the calculation of performance metrics, such as accuracy (ACC) and Matthews correlation coefficient (MCC); and result prediction, generating a seismic cube with the fractures identified at each seismic node. The possibility of feedback is indicated at the end of the process, being performed for the approved predictions. It is noted that the process can iterate multiple times, increasing the network's complexity.

Results

The implemented code allows for great configuration flexibility to address the problem. Thus, several approaches could be evaluated by defining various training scenarios, using different data augmentation techniques, different filtering frequencies for the P32 logs, different test set scenarios, and different network architectures. These scenarios refer to the combination of each of the cases described below. It is important to note that smaller network architectures and cube dimensions are necessary to avoid overfitting due to the limited amount of annotated data available. Therefore, convolutional layers are not initially applied, as these layers have too many free parameters for this application. Only two fully connected network architectures are initially analyzed: 4x4x2 and 8x4x2, where each value refers to the number of neurons in the corresponding layer. Convolutional layers are explored after sufficient data is available through feedback/data augmentation steps.

- **Data Augmentation Scenarios:**
  - I: Original data
  - II: Original and rotated data
  - III: Original and inverted data
  - IV: Original data modified by multiplying the amplitude by a constant
- **Cutoff Frequency Percentages:**
  - percf06: Covers 60% of the frequency spectrum
  - percf08: Covers 80% of the spectrum
  - percf1: No filtering
- **Validation Methods:**
  - A: 3 wells for training and 10 for testing
  - B: 8 wells for training and 5 for testing
  - C: 10 wells for training and 3 for testing
  - D: 80% of the samples for training and 20% for testing
- **Two Fully Connected Network Architectures:**
  - 4x4x2: Layers with 4, 4, and 2 neurons, respectively
  - 8x4x2: Layers with 8, 4, and 2 neurons, respectively

The results of the different test set scenarios (Figure 2) show median MCC values close to zero, with some results even reaching negative values. They indicate that the initial networks cannot make reliable predictions for the entire seismic volume (cases A, B, and C). However, the predictions near the training data might be useful (case D). This outcome is particularly interesting from the perspective of the use of predictions as new training data.

Figure 3 illustrates the results obtained based on the data augmentation techniques employed. The tested scenarios show that these techniques add little helpful information to the predictions beyond what is already contained in the original data (case I). The data augmentation scenario involving brightness adjustment (case IV) shows better results. Still, these are more likely artifacts related to using modified data in training and test sets rather than a real positive effect of data augmentation.

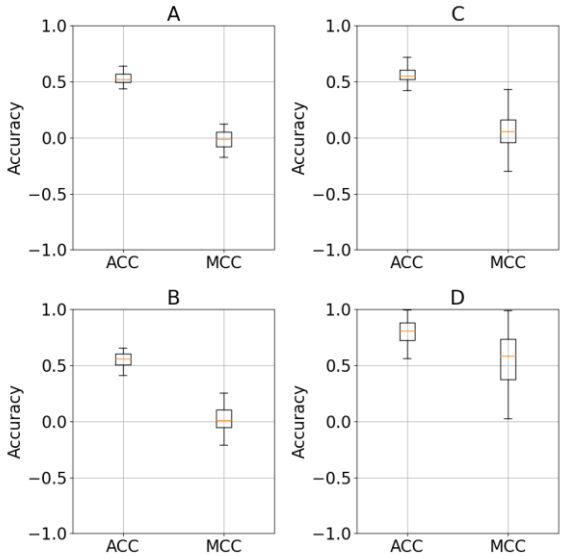

Figure 2 - Results obtained for each validation scenario, where ACC is accuracy, and MCC is the Matthews correlation coefficient.

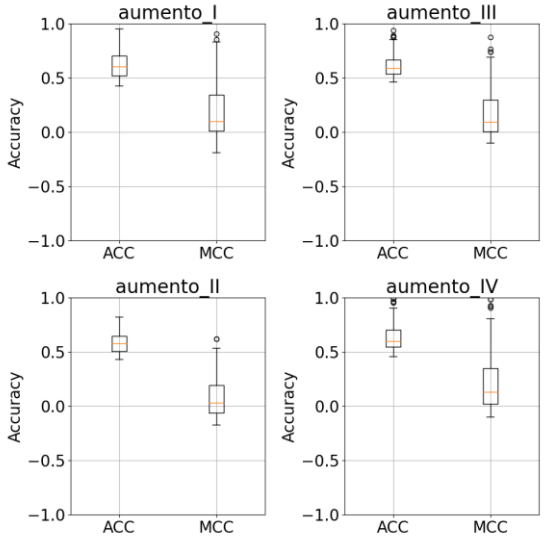

Figure 3 - Results obtained for each of the data augmentation scenarios.

In Figure 4, it is evident that the percentage selected for the filtering frequency significantly impacts the learning results, especially when comparing the unfiltered case (percf1) with the others (percf06 and percf08). In this comparison, it is observed that the lower MCC limit of the last two cases surpasses the upper limit of the unfiltered case.

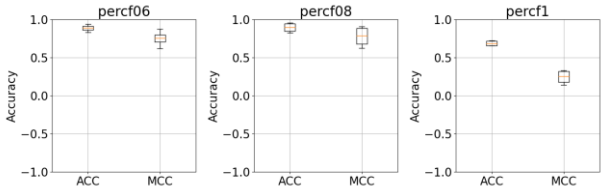

Figure 4 - Results for the scenarios with different filtering frequency percentages.

Figure 5 presents the resulting predictions for scenarios covering three different frequency percentages to illustrate the type of response generated by the methodology. It is evident that the choice of cutoff frequency for filtering significantly influences the reported results.

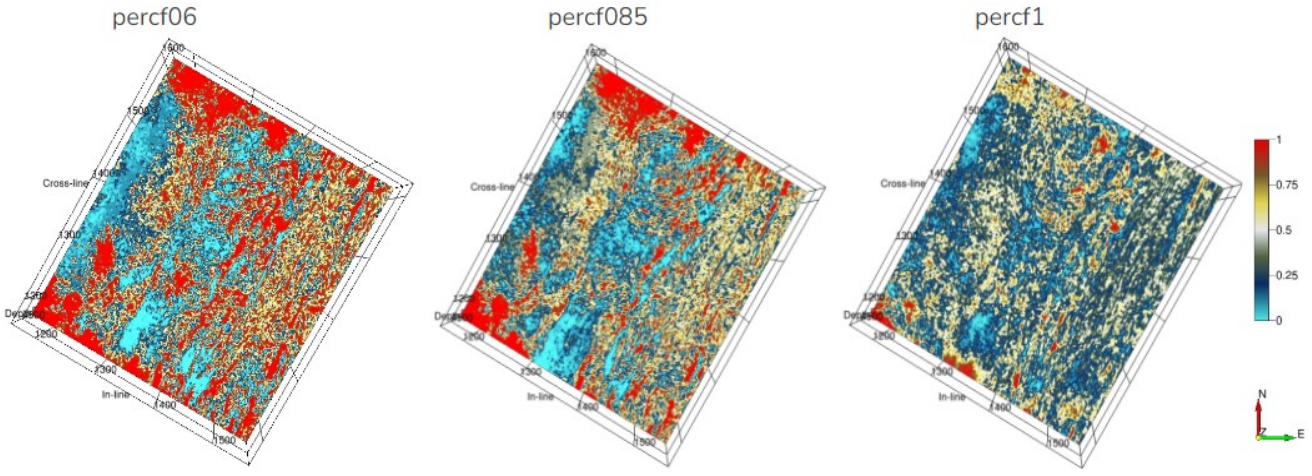

Figure 5 - Predictions made for models trained with the 6x2 architecture, using training data from scenario D, with only original data (no data augmentation), for frequencies associated with three different percentages (0.6, 0.85, and 1).

For an initial assessment of the potential of feedback, a validation procedure was employed based on the prediction value associated with each point. These values are continuous, ranging from 0 to 1. Predictions in four different scenarios (percf06, percf085, percf095, and percf099) around the wells used for training were selected as the basis. Only predictions where all models agreed, considering a threshold of 0.02, were selected. Figure 6 illustrates this selection process, with the filtered data indicating the points effectively approved for feedback. Although only a small proportion of data meets the established criteria, they represent 30 times more data than initially annotated, allowing for the use of larger networks in a self-supervised training approach.

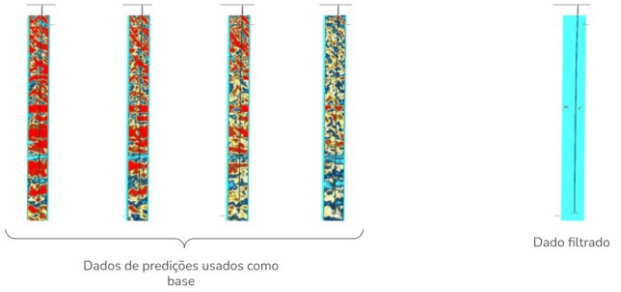

Figure 6 - Different predictions around one of the training wells and the filtered data for self-supervised training. Only a few points meet the adopted criterion (filtered data).

The training results based on networks trained with these data are presented in Table 1. This table shows the tested network architectures using the same definition pattern mentioned in the first test, as well as the same quality metrics employed previously. It can be noted that the complexity of the network architectures used, measured by the total number of neurons present, is much higher than the original ones due to the increased number of annotated data enabled by self-supervised training. The quality coefficients indicate that both models could extract relevant patterns for the problem but have not achieved results that justify an immediate practical application.

Table 1 - Results for the network trained with self-supervised training.

Architecture	ACC	MCC
20x12x6x4x2	0.64	0.40
10x8x4x2	0.62	0.36

Naturally, the data selection process for self-supervised training is an example of how the process is conducted. For better results, experts must evaluate and validate the data entering the self-supervised training process.

Discussions and conclusions

This work aimed to develop a methodology for predicting fractures using machine learning and seismic pre-stack data with full azimuth coverage.

The analyses conducted indicate that the simple network architectures (4x4x2 and 8x4x2), trained using only the available annotated data, are not capable of making reliable predictions for the entire seismic volume. A high rate of fractures was predicted in regions where such occurrences were not expected, along with a strong correlation of predictions with seismic horizons. On the other hand, the quality metrics obtained for predictions related to data in the vicinity of those used for training show promising values. Thus, the methodology is on the right track but needs further refinement for practical use.

It is also observed that the processing of annotated data significantly impacts the application's response, particularly concerning the selection of cutoff frequency for filtering. Data augmentation did not considerably influence network quality at this stage. The effect of data augmentation should be re-evaluated with larger networks if self-supervised training is pursued.

The process of self-supervised training with predicted data near the training wells is a promising option for improving the model. An initial study of this process suggests that more complex networks could be employed, potentially even convolutional layers. However, further studies are needed regarding the data validation process for self-supervised training, especially from an expert's perspective. Additionally, it is essential to continue working with the developed methodology and conducting new analyses to achieve results with practical relevance.

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