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Analysis of Seismic Attributes to Assist in the Classification of Salt by Multi-channel Convolutional Neural Networks

F. Jiang[1]*, P. Norlund[1], Z. Wei[1]

[1] Halliburton

Summary

Recently, many deep-learning approaches have been applied to geophysical problems, such as seismic processing and interpretation, to aid in the exploration of hydrocarbon reservoirs. Convolutional neural networks (CNNs) are a popular new method to identify salt bodies in seismic data, by analyzing image segmentation and feature extraction. In this study, four ensemble classifiers were trained to analyze the importance of various seismic attributes with respect to the predictability of a salt body. By choosing seismic attributes with the highest importance as input data to a multi-channel CNN architecture, we successfully improved the accuracy of salt prediction. Both binary and multi-label salt classifications are shown, as well as comparisons of salt classification probability maps generated from models trained by seismic-only data vs models trained using seismic-plus-attributes data. The results demonstrated that using seismic-plus-attributes models significantly improved the continuity of salt boundaries and reduced unwanted artifacts, whilst also converging faster during training.

Introduction

Machine learning approaches to geophysical interpretation have recently shown success in automating the identification of structures in seismic data, which in turn can help reduce the time required for the interpretation life-cycle. For example, Convolutional Neural Networks (CNNs) have been shown to be capable of identifying features such as salt boundaries, faults, and facies in seismic data (Wang et al., 2018). However, the varying quality of seismic data can affect the prediction accuracy. A low resolution of predicted seismic features can lead to multiple issues, including failing to correctly identify potential drilling hazards.

Traditionally, physics-based approaches to seismic interpretation have played the predominant role in geophysical analysis. Some examples include semblance-based fault interpretation (Hale, 2009) and horizon tracking by instantaneous phase picker (Li, 2000). Those interpretation algorithms are based on individual seismic traces and their derivatives rather than looking for patterns as a human interpreter might. As datasets get larger, and features get more complex, using individual seismic traces, or groups of traces, may not be the most efficient or effective way to analyze seismic data. As an alternative, CNNs represent a new approach to directly analyze seismic images pixel-by-pixel to identify various geological features. Di et al. (2018) discussed the superiority of CNNs in learning and identifying local seismic reflection patterns to build the mapping relationship between the seismic signals and the target structures.

Seismic attributes are frequently used to help identify geological features in seismic data. Many attributes have been developed to assist geological interpretation (e.g. Marfurt and Kirlin, 2000; Hale 2009). Guillen et al. (2015) used the second derivative and curve length from seismic data to assist the ensemble approach for salt detection, while Shafiq et al. (2016) developed a saliency-based attribute to detect salt domes within seismic volumes. In this study, we calculated thirty well-known seismic attributes and then analyzed the importance of each attribute with respect to the predictability of a target salt body. The seismic attributes with the highest importance factors were then used as additional channels to feed into a multi-channel CNN architecture. Several tests between a seismic-only model and a seismic-plus-attributes model showed that training on a combination of seismic data and attributes helped to improve the accuracy of salt body prediction, especially when using a multi-label salt classification dataset.

Method

In this study, we selected a subset of the SEG Advanced Modeling (SEAM) seismic dataset as a benchmark to analyze the importance of each attribute using four ensemble classifiers. Ensemble learning is a supervised learning to classify new data points using a weighted vote for their predictions and to provide a ranking of the results (Dietterich 2000). Thirty well-known seismic attributes were calculated, with each attribute belonging to one of five sub-categories: Amplitude, Phase, Frequency, Structure, and Other. Each attribute was then used as a training dataset along with a labeled salt volume and fed into four different ensemble classifiers: Random Forest classifier (RFC), Decision Tree Classifier (DTC), Gradient Boosting Classifier (GBC) and Extra Tree Classifier (ETC) (Figure 1). By running each attribute through each classifier separately, the relative importance of the attribute with respect to the predictability of the salt body could be calculated. The seismic attributes with the highest importance rank were then used as additional channels to assist in salt classification in a multi-channel deep-learning neural network.

Figure 2 shows a comparison of importance factors between the different ensemble classifiers. The number along the x-axis represents the index of a seismic attribute as marked in Figure 1. The order of rankings varies between the different classifiers. However, four attributes were present within the highest ranks for all of the classifiers: response amplitude, response frequency, relative amplitude change, and apparent polarity. These four attributes consistently predicted the salt body regardless of classification method used.

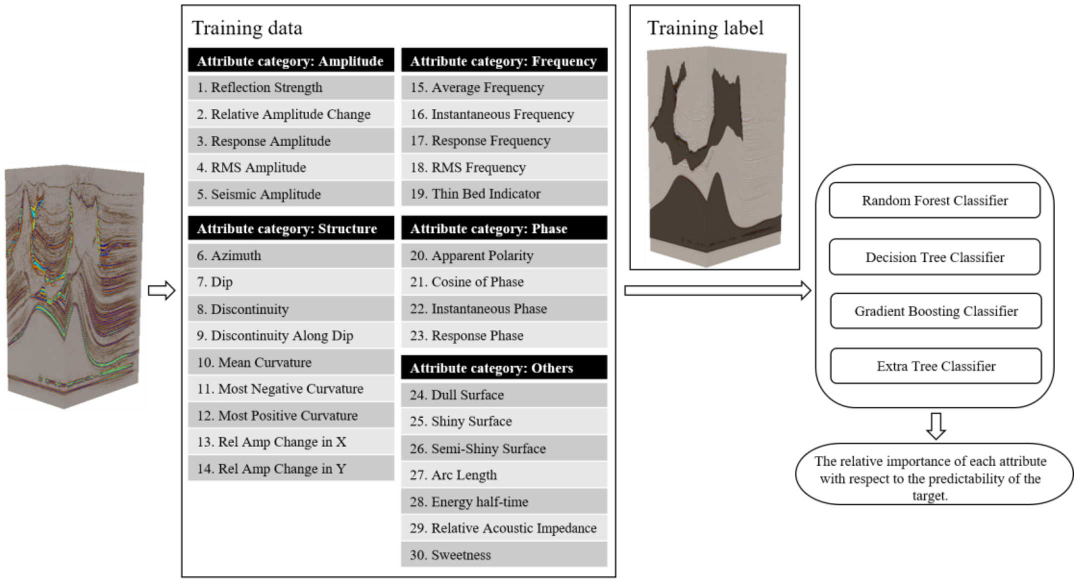

Figure 1 *A workflow to identify the relative importance of seismic attributes for salt detection.*

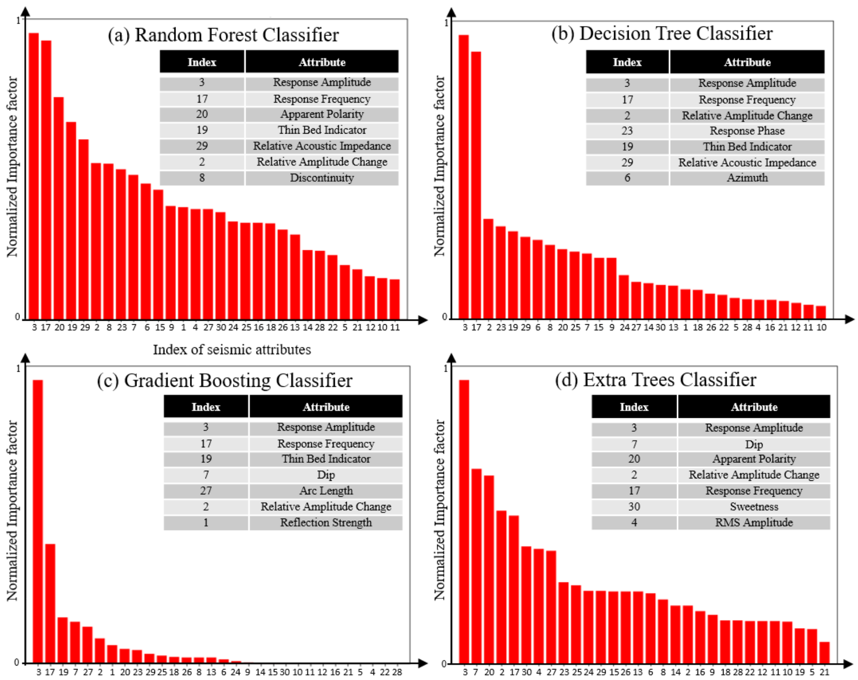

Figure 2 *The normalized rank of seismic attributes by four ensembled classifiers. The tables show the attributes with the highest importance factors for each classifier.*

Those four attributes, along with the original seismic data, were then fed into a modified U-Net (Ronneberger et al. 2015) architecture. Our modified U-Net, including a multi-channel residual learning framework, max pooling layers, dropout layers, and a softmax loss function, is designed to improve accuracy. Our tests show that seismic-plus-attribute models consistently improved the prediction accuracy with fewer artifacts, especially for multi-label salt classification.

Examples

We used the synthetic SEAM data to train the models. Additional tests using real data will be presented in future publications. The SEAM data represents the deep-water regions of the Gulf of Mexico, containing sediments with similar amplitude values to the salt body, which brings additional challenges to the interpretation process. The four seismic attributes were generated using our in-house software, and two different label volumes were generated: a binary model identifying salt vs no-salt, and a multi-label volume identifying water, shallow-salt, deep-salt, sediment, and basement. We used a 5% subset of the data for training, and trained both a binary model and multi-label model with and without the four attributes. We then used each model to classify the remaining 95% of the data (Figure 3).

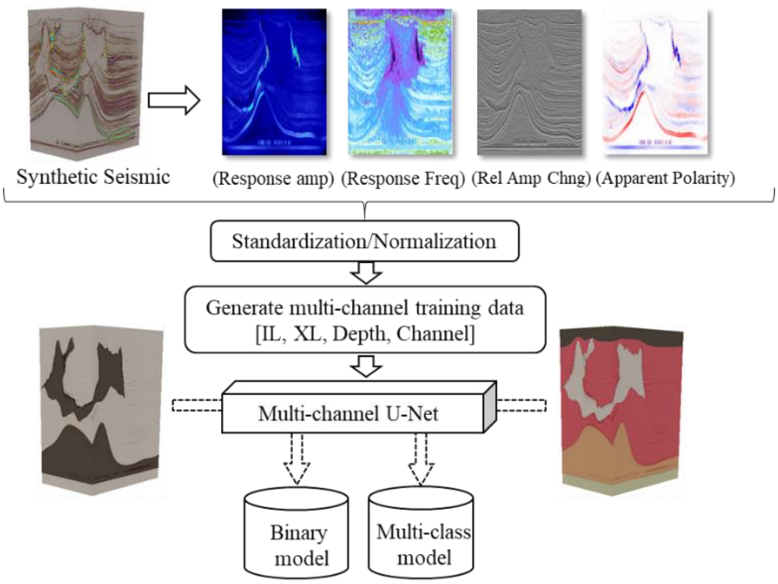

Figure 3 *A workflow to implement multi-channel U-Net for binary and multi-label salt classification.*

Figure 4 compares the results of a binary classification between the seismic-only model (Fig. 4a) and the seismic-plus-attributes model (Fig. 4b). The prediction accuracy improved from 87% to 90% when using the seismic-plus-attribute model. Several areas with false prediction were corrected, the salt boundary was better defined, and results took fewer epochs to converge.

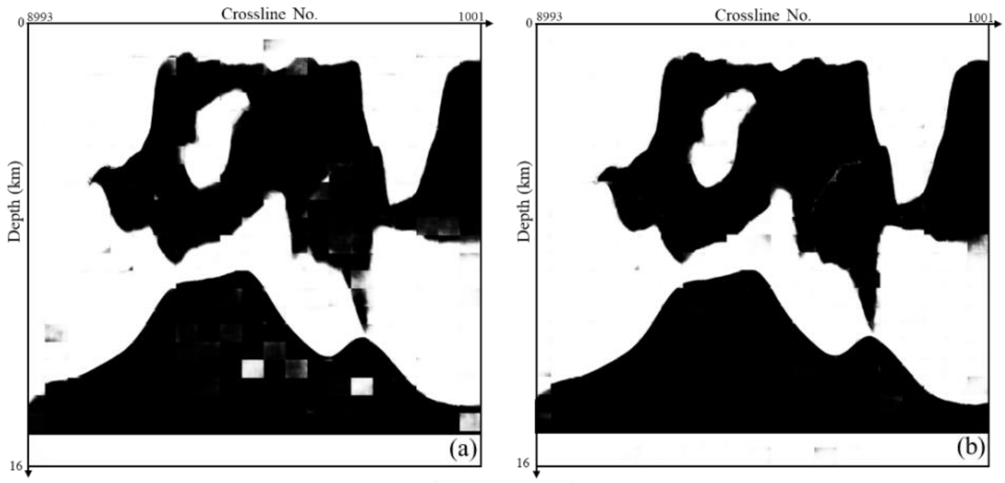

Figure 4 *A binary classification between (a) prediction by seismic-only model and (b) prediction by seismic-plus-attribute model.*

Figure 5 compares the results of multi-label salt classification between a seismic-only model (Fig. 5a) and a seismic-plus-attribute model (Fig. 5b). The classification results from the seismic-plus-attribute model showed much cleaner classified facies with many fewer false predictions. The salt boundary was also delineated more continuously compared with seismic-only model. Training of the seismic-plus-attribute model took similar computation time to the seismic-only model but required significantly more memory to allocate the additional attributes as input channels. To solve this memory issue, we developed an iterative workflow which allowed us to train the model as a series of small subsets.

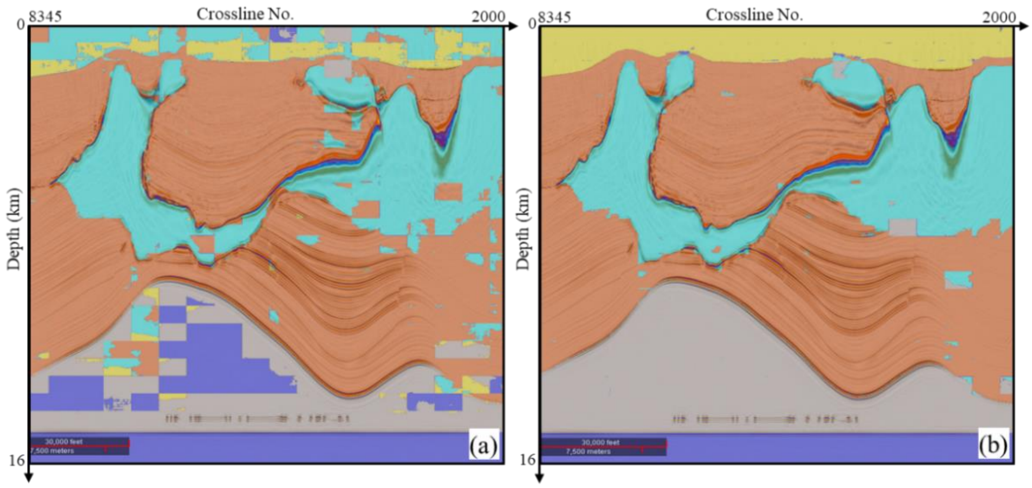

Figure 5 *Multi-label salt classification between (a) prediction by a seismic-only model and (b) prediction by a seismic-plus-attribute model. Yellow: water; Cyan: shallow salt; Grey: deep salt; Orange: sediment; Purple: basement.*

Conclusions

In this paper, we have demonstrated an attribute-assisted multi-channel U-Net architecture for salt prediction. Four different ensemble classifiers were implemented to analyze the relative rank of seismic attributes with respect to the predictability of a salt body. Several attributes with the highest rank were then chosen as additional channel inputs to train a deep-learning model. We demonstrated that seismic-plus-attribute models can significantly improve the accuracy of salt prediction with fewer artifacts, especially for multi-label salt classification. With the help of seismic attributes, geological features can be identified more accurately by neural networks, helping reduce the total time required to interpret seismic data sets.

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