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Seismic Attribute-Guided Automatic Fault Prediction by Deep Learning

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Summary

Fault identification in seismic data is a vital but time-consuming step in the seismic interpretation workflow. Recent studies demonstrate how deep-learning techniques, such as convolutional neural networks (CNN), can be used to automatically identify these faults with high accuracy. However, different levels of signal-to-noise ratios in seismic data can degrade prediction accuracy. A low resolution of predicted faults can cause multiple issues, such as failing to identify potential drilling hazards. In this abstract, a workflow is developed to combine the seismic data with multiple seismic attributes to train machine-learning models using a multichannel CNN architecture. A random forest is implemented to analyse the selection of each attribute in terms of a feature importance factor. Several attributes with a high-importance factor are selected as additional channels to feed into the multichannel CNN architecture. A comparison of fault predictions between a probability map generated from a model trained by seismic-only and a model trained using seismic-plus-attributes is presented. The results exhibit significant improvement on the continuity of fault segments and reveal missing fault planes not identified using a seismic-only model. Additionally, a modified generative adversarial network is implemented to reconstruct the fault probability map to help improve the resolution.

Introduction

Fault identification in seismic data is a vital but time-consuming step in the seismic interpretation workflow. Recent studies demonstrate how deep-learning techniques, such as convolutional neural networks (CNN), can be used to automatically identify these faults quickly with high accuracy. However, different levels of signal-to-noise ratios and other artifacts in seismic data can degrade prediction accuracy. A low resolution of predicted faults can cause multiple issues, such as failing to identify potential drilling hazards.

Seismic attributes, quantities calculated from seismic data, are frequently used to analyze and enhance the quality of geological or geophysical interpretations. Many attributes have been developed to assist fault interpretation (Marfurt and Kirlin 2000; Hale 2009). Those methods can be considered traditional computer-aided approaches to assist human interpretation. With recent developments in image recognition and target identification research, a neural network approach has become an effective tool to assist geophysical feature interpretation, particularly in automatic fault prediction. Zhang et al. (2019) developed a deep CNN model for 3D fault picking, which also helps predict fault dip and azimuth information. Zhao (2019) implemented a CNN architecture to detect faults while estimating fault orientation from fault probability.

For this abstract, a workflow is developed to combine original seismic data with multiple attributes to train machine-learning models using a multichannel CNN architecture. A random forest (RF) architecture is implemented to analyze the selection of the best seismic attributes to assist fault identification. The selected attributes are considered additional channels to feed into a multichannel CNN architecture. Finally, a generative adversarial networks (GANs) (Goodfellow et al. 2014)-based post-processing reconstruction workflow is applied to help eliminate blurry effects and improve the resolution of the predicted fault probability map. Two examples are illustrated to exhibit the improvement of prediction results compared to the seismic-only CNN architecture.

Method

CNN has shown to be good for image recognition and feature extraction in computer vision. The U-Net architecture (Ronneberger et al. 2015) was designed for image segmentation in biomedical images and has become a popular tool for seismic interpretation, particularly in the areas of salt detection, fault prediction, and facies classification. The traditional U-Net architecture adopted extends the input layer to allow seismic attributes as additional channels (Figure 1). A synthetic data generator (Wu et al. 2019) is implemented to create various seismic volumes, attributes, and fault labels and to train a 3D multichannel U-Net for fault prediction.

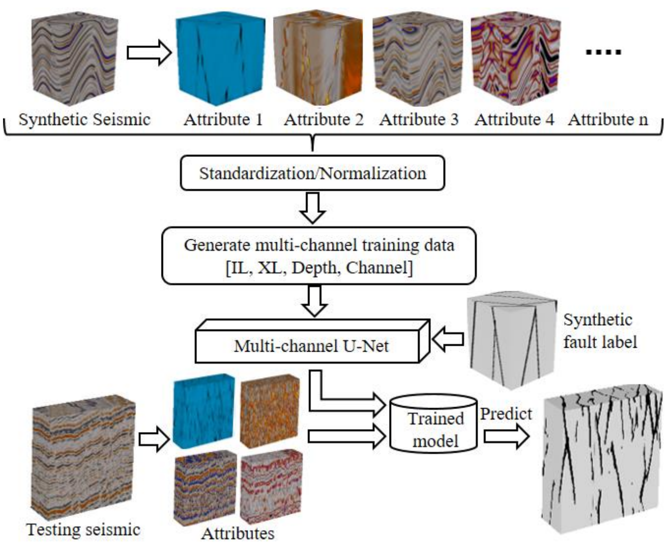

***Figure 1**: Workflow of attribute-assisted automatic fault prediction.*

During training, seismic attributes serve as a guide to provide detailed structural information in the encoder from U-Net. The U-Net decoder reconstructs the extracted feature to identify where the fault should exist. More than 30 seismic attributes belonging to several different categories (i.e., amplitude, phase, frequency, or structure) were generated. A RF, a decision-tree-based approach, is implemented to calculate the importance factor for each attribute and to demonstrate how important each attribute is in generating a fault probability map. The selected attributes identify both discontinuity in seismic data and the continuity of amplitude events. Figure 2 shows a chart of feature importance, indicating the most important attributes for fault identification purposes with related standard deviation. The attribute "discontinuity along dip" shows the highest importance factor among the attributes, accounts for reflection dip, and produces cleaner images than standard discontinuity (Hale 2009), which highlights faults, channels, and diapirs.

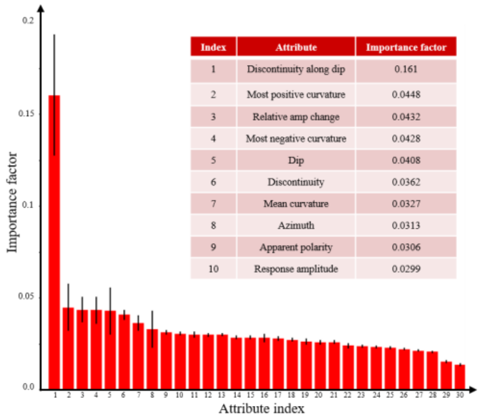

***Figure 2**: Feature importance of seismic attributes.*

The attribute "most positive curvature" records the most positive rate of change of the reflection dip and azimuth, highlights reflection bumps in seismic reflections, and is closely related to the attribute "most negative curvature", which highlights reflection sags. Normal faults often exhibit positive curvature on the up-thrown side and negative curvature on the down-thrown side. The "relative amplitude change" attribute serves as a directional high-resolution discontinuity attribute that reveals details in faults and channels along time or depth and exhibits similar effects to the coherence amplitude gradient (Marfurt and Kirlin 2000). Attributes with a high-importance factor are recognized as good attributes to assist fault prediction and treated as additional channels to feed into a multichannel U-Net. Those attributes can be calculated before the prediction step using various commercial software tools. The multichannel U-Net has the ability to use any available attributes, and in our tests, four attributes are implemented that have the highest rank (Figure 2). A standardization scalar is applied to centralize and scale each feature by computing mean and standard deviation.

Deep-learning prediction results always have a low-probability component, which shows as blurry images on a fault probability map and affect the ability to extract complete fault planes. Implementing an amplitude threshold approach to decrease blurry effects is not effective because there is ambiguity in defining an optimal amplitude threshold value. A GANs-based super resolution algorithm was implemented to help eliminate the blurry effects. This adversarial model can automatically discover and learn the regularities and patterns from input fault probability maps to mimic data distribution. This GANs-based fault clarification workflow can be used as a standard post-processing step to help eliminate low probability and can potentially be extended to other deep-learning prediction results where low probability exists.

Examples

To train a multichannel U-Net model, multiple synthetic seismic cubes, attributes selected by the importance factors, and fault labels were generated. To compare the prediction result, two U-Net models were trained: the first model only contained seismic and fault label data, and the second model contained seismic, multiple attributes, and fault label data. The remaining network layers were kept exactly the same between the two models to avoid any discrepancy during training. To train the model with multiple attributes, an iterative data generator workflow was implemented to optimize the consumption of system and GPU memory allocation. The final trained multichannel model could be treated as a general model to help predict fault probability maps from different seismic surveys. The proposed approach was applied to two different seismic surveys—Indian 3D 2000 MSS, provided by the Australian government, and OPUMAKE 3D from the Taranaiki Basin, provided by New Zealand Petroleum and Minerals.

Figure 3 shows the comparison of fault prediction from the Indian 3D 2000 MSS survey. Figure 3a used a seismic-only trained model to help predict the fault probability map, and Figure 3b used a model trained using seismic plus multiple attributes to help predict the fault probability map. It was observed that fault segments predicted by seismic-plus-attributes exhibit a good improvement, marked by the white arrows, compared to faults predicted by seismic only. The result shows an improvement in the continuity of fault segments and reveals several missing fault segments.

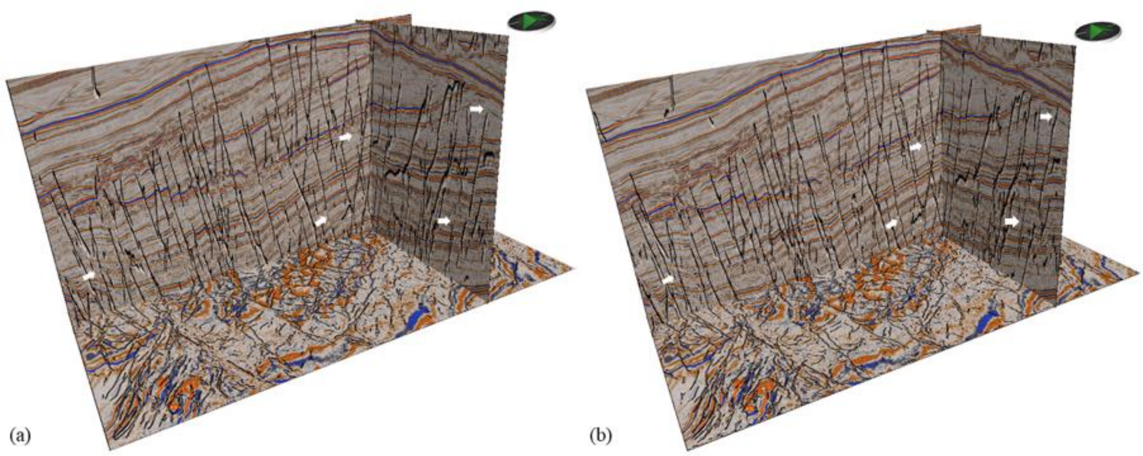

***Figure 3**: Comparison of predicted fault probability map between (a) predicted by model trained from seismic only and (b) predicted by model trained from seismic plus attributes on Indian 3D 2000 MSS survey.*

Figure 4 shows additional prediction results from the OPUMAKE 3D data set. The proposed model creates clearer fault images with less noise compared to the seismic-only model. Figure 4b shows several fault segments (highlighted by the white arrows) on a depth slice that are predicted and extended further along a seismic discontinuity.

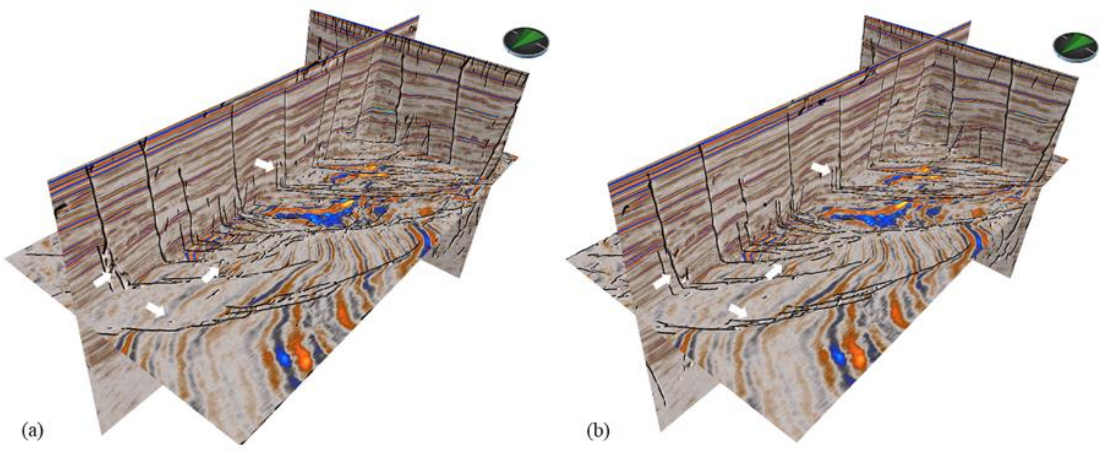

***Figure 4**: Comparison of predicted fault probability map between (a) predicted by model trained from seismic only and (b) predicted by model trained from seismic plus attributes on OPUMAKE 3D survey.*

Fault prediction results from deep learning are often characterized by low-resolution fault probabilities that extend fault-like images beyond the true fault-plane range. The low fidelity of the fault prediction results can create uncertainty when locating the true fault. We implement a GANs-based algorithm to help improve the resolution of the fault probability map. A weighting matrix is added to scale up the amplitude of the local patterns. The reconstructed fault segments exhibit thinner and clearer segments (Figure 5). The application of GANs is not limited to reconstructing and clarifying fault probability maps, it can also be used to reconstruct other seismic features to help improve their resolution, such as salt bodies and multifacies prediction results.

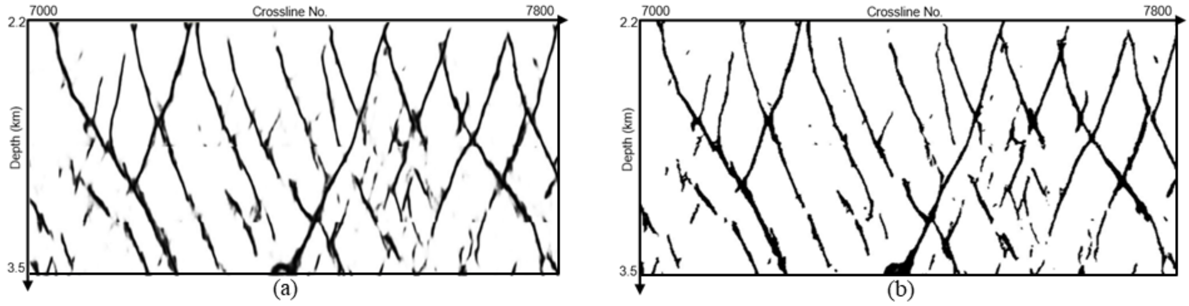

***Figure 5**: Comparison of multiattribute prediction results. (a) Before applying GANs-based approach and (b) after applying GANs-based approach on Indian 3D 2000 MSS survey.*

Conclusion

For this abstract, a multichannel U-Net architecture was implemented to help improve the prediction accuracy of fault probability maps. A decision-tree-based analysis of the feature importance helped identify the most important attributes as additional channels to feed into the network. By training with seismic and multiple attributes simultaneously, the approach helped successfully improve prediction results to identify more continuous fault segments and predict missing fault segments that are not estimated using a seismic-only trained model. Implementing a GANs-based reconstruction approach further clarifies fault locations and helps eliminate low probability blurred areas, providing a higher quality fault probability map.

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