The Use of Machine Learning to Enhance Faults and Fractures Detection in Seismic Data

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Faults and fractures are key elements that control the fluid flow in porous rock layers and as a result the oil production. Conventional methods to identify faults and fractures are time consuming, have limited resolution and can be costly at the same time. Such limitations have motivated many scientists and engineers in the industry to try to find an alternative approach.

The intelligence system on the basis of machine learning has been used by many geoscientists recently to predict and extract geological information from seismic data. For this purpose, we used the artificial neural network approach. Raw seismic data is not immediately useful as an input data to the neural network. A post stack filtering process applied to the seismic data was necessary to remove undesired noise and enhance the faults visibility. The new filtered seismic volume was then used to compute other discontinuity-sensitive attributes to be used for training the neural network. Meta attributes, which refers to a combination of attributes, are used to enhance the detection of geologic features such as faults and fractures. The supervised neural network is designed to choose and combine the most responsive attributes (i.e. similarity, fault likelihood, curvature).

This is performed by training the neural network using a set of 3D locations at identified fault and non-fault locations. During the training mode, the neural network will recognize combinations of seismic attributes that are predictive for areas of high fault probability and areas of low fault probability. Using Thinned Fault likelihood (reference) as razor-sharp fault image attribute, fault visualization was improved. The trained artificial neural network was applied to the whole seismic volume in order to generate a cube of fault probability. When the fault probability volume is superimposed on the seismic data, results indicate that faults and fractures are detected with more clarity and precision.

Introduction

With the increase of data size in the oil industry, seismic interpretation and attribute computation require significant amount of time and efforts. Artificial intelligence is a useful tool in such cases because it can handle large data sets and also understands the relationship between various data more efficiently. Machine learning can be divided into supervised and non-supervised subsets. The most commonly network type used is the supervised learning, in which the interpreter provides the training data "labels" as well as the seismic attributes.

The objective of this study is to detect faults and fractures in conventional and unconventional data using machine learning. For this purpose, a supervised neural network is used for seismic object detection. The most common Artificial Neural Network (ANN) model is the multi-layer perceptron (MLP) with the learning algorithm which provides a non linear relationship between the input and the target output of the training data (Aminzadeh, and de Groot., 2006). The MLP neural network consists of at least three layers, an input layer, a hidden layer and an output layer

(Figure 1). This model of neural network is designed to choose and combine the most responsive attributes (i.e. similarity, curvature, and semblance).

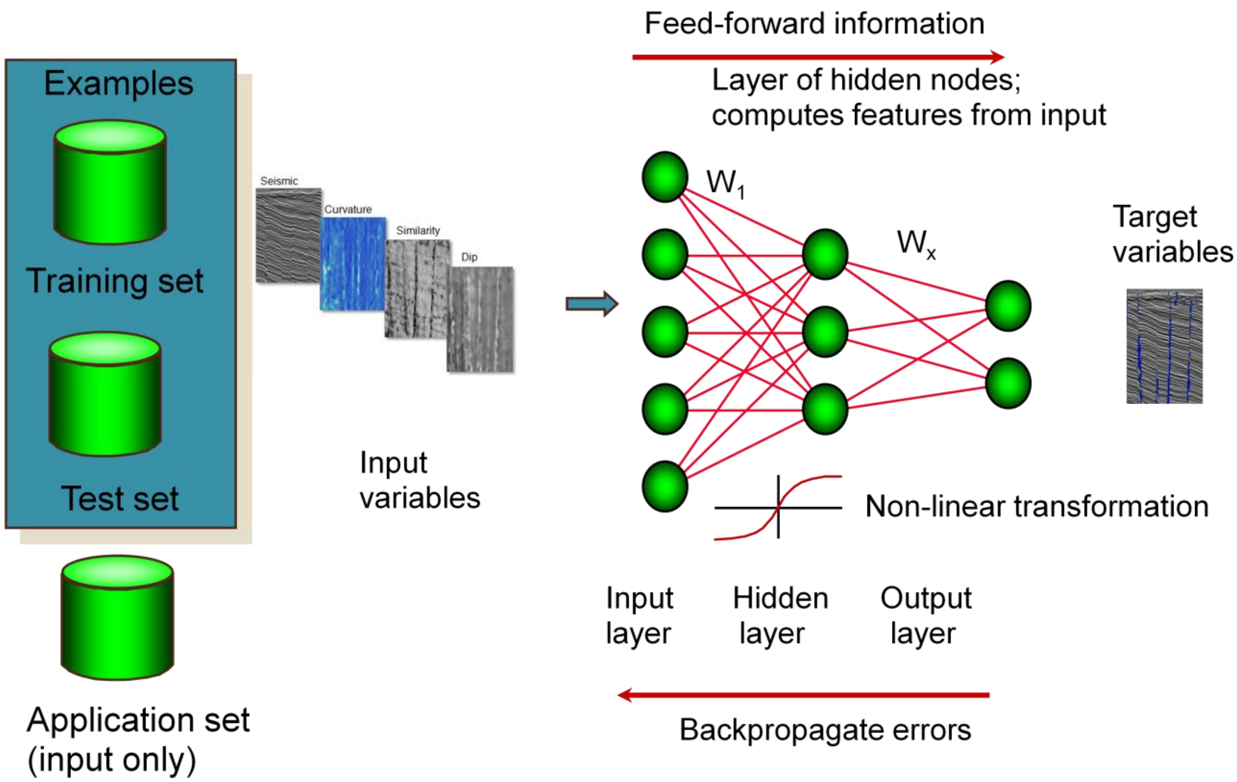

Figure 1. Simple feed-forward artificial networks with input and output layer.

Methods and data enhancement

The data conditioning procedure is aimed to clean up the data from any undesired noise and to enhance the lateral continuity of seismic reflectors. This was carried out in two steps, in the first step a dip volume was created using a Fourier transform based algorithm. The dip was then used as a guide to compute a median filter. Figure 2a shows the raw seismic. Figure 2b shows the result after applying a median filter to remove the undesired noise. The new filtered seismic data (Figure 2b) was scanned to identify the location of the faults and used to compute other discontinuity sensitive attributes. Once these geological features are located, a number of 3D points that represent the faults and non-faults are selected on a key seismic line. A combination of seismic attributes that are predictive of seismic discontinuity or faults will be computed at these locations. This information is used to train the neural network in order to predict the fault probability of a full 3D dataset.

Attribute extraction and Machine learning

Our goal of using machine learning in seismic interpretation is to teach a model to identify seismic objects in the data. Our workflow here is based on number of steps.

- We extract features (attributes) to find as much information as possible about the seismic object of investigation.
- Select training data.
- Train the neural network.
- Applying final result on the entire data.

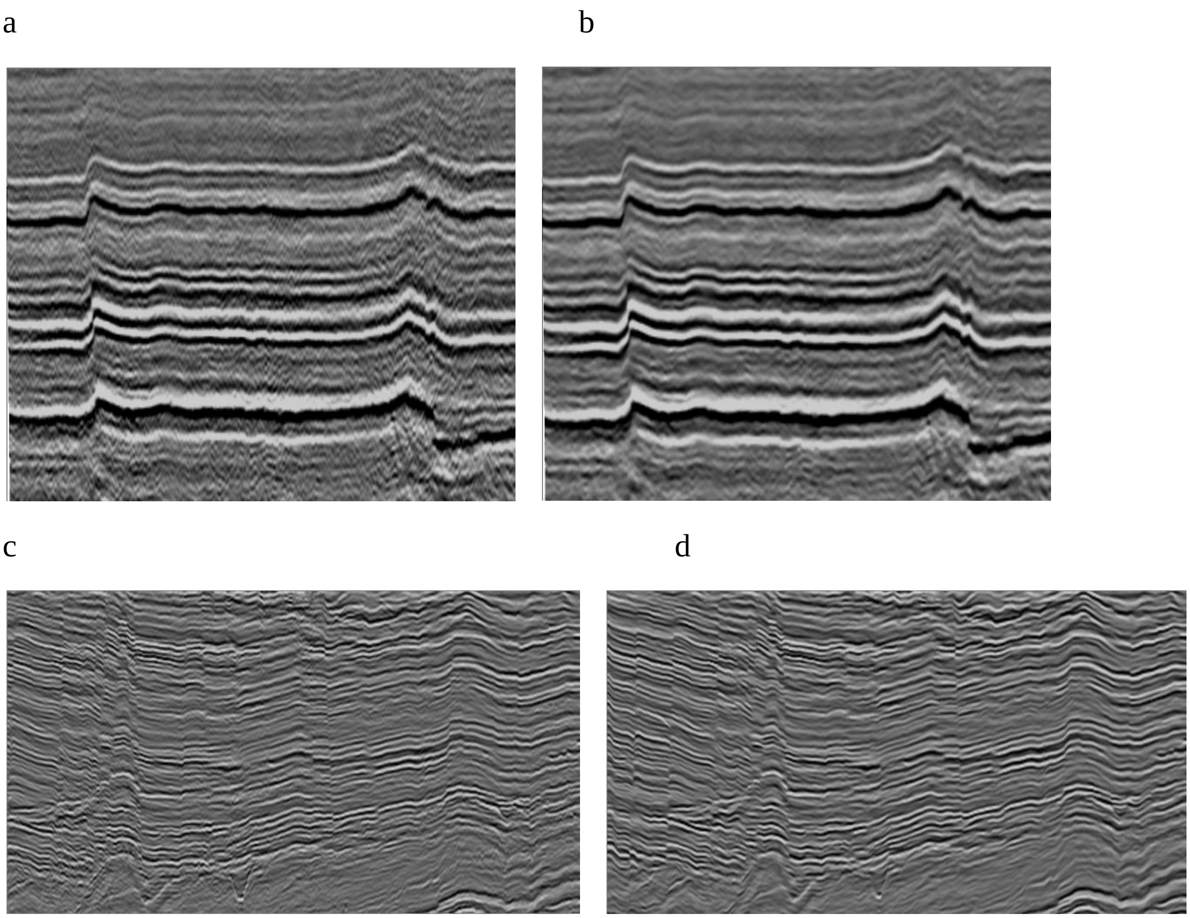

Figure 2. Data conditioning results are displayed on two seismic sections. Figures a and c show the initial seismic sections from Firestone 3D and Kerry field, respectively, before filtering. Figures b and d show seismic sections after dip steered median filtering was applied. Data was enhanced and Faults appear more conspicuous.

Seismic attributes have become very popular among the geosciences community in the 90s, and have been dramatically developed ever since. A single attribute often shows more information than the object of interest (e.g. faults). Meta attributes, which refers to a combination of attributes, are a solution to this problem can be used to enhance the detection of geologic features such as faults, fractures, channels, and salt bodies (Brouwer et al., 2011). For the purpose of this study, the most fault sensitive attributes were used to create the meta attributes. Attributes such as similarity, coherency, and curvature examine the extent to which seismic trace segments differ from each other (Bahorich and Farmer, 1995). Such seismic-discontinuity attributes detect the abrupt lateral changes in the seismic data caused by faults.

Machine learning is performed by training a neural network using a set of 3D locations at identified fault and non-fault locations from the seismic section. The performance of the neural network is monitored by computing a normalized RMS and a misclassification. The RMS curves indicate the overall error in the training and test sets. The misclassification shows the percentage of points of the training and test sets that is classified in the wrong class. RMS and misclassification are computed on both test and train data.

During the neural network training it is important to find a proper stopping point to avoid over fitting. Figure 3 explains the stopping criteria for neural network training. The neural network combines multiple attributes into a single fault probability attribute which is able to highlight the faults and fractures. The neural network results can be validated before computing the 3D fault cube. A confusion plot or matrix is a way we used to check the quality of the neural network. Once the final neural network is validated, we generated the 3D fault volume that optimally images the faults in the seismic data.

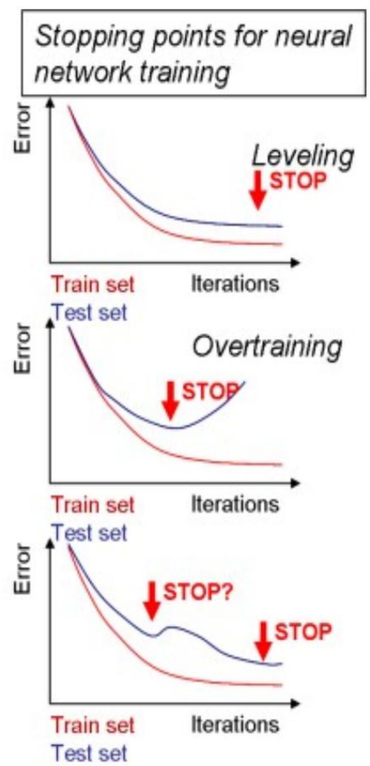

Figure 3. The stopping criteria for the neural network training (Brouwer et al., 2011).

Case Study 1

This study focuses on an unconventional reservoir in the northern side of Ohio State. The target zone is Utica shale- Point Pleasant formation. Utica shale, Late Ordovician calcareous shale, is one of the most prolific unconventional reservoirs in US. The data set is from the Firestone field in which the seismic was acquired in 2012 to illuminate the Utica shale play. Utica shale and the underlying Point Pleasant are organic rich formations and contain considerable amount of natural gas underneath. Tectonically, the basement structure of the Appalachian basin and the Rome trough are controlling the depositional and the burial history of the Utica- Point Pleasant formations (Harper and Laughrey, 1987). Our goal is to predict the area of fractures intensity which could lead to potential sweet spots for drilling using machine learning. We trained our neural network on number of labels, and 20% of the training data is set for model selection and validation purposes. The labels are represented by the nodes that are picked on a seismic line shown in figure 4. Once the model parameters are selected, we retrain our neural network on the entire training data set. Then, we applied on the entire 3D seismic volume to predict the distribution of fracture density along Utica/Point Pleasant formation. The neural network final result was applied on Utica/ Point Pleasant formation as shown in figure 5a. The figure shows the distribution of faults and fractures on the Utica shale interval. The results illustrate clearly the areas where the fracture density is high and the areas with a low or even zero probability. Additionally, when we use the thinned fault likelihood attribute combined with other meta attributes, the fractures stands out very clearly (Figure 5b) (Hale et al., 2013). The area with a high fracture density may indicate a potential well drilling location (Refayee et al., 2016).

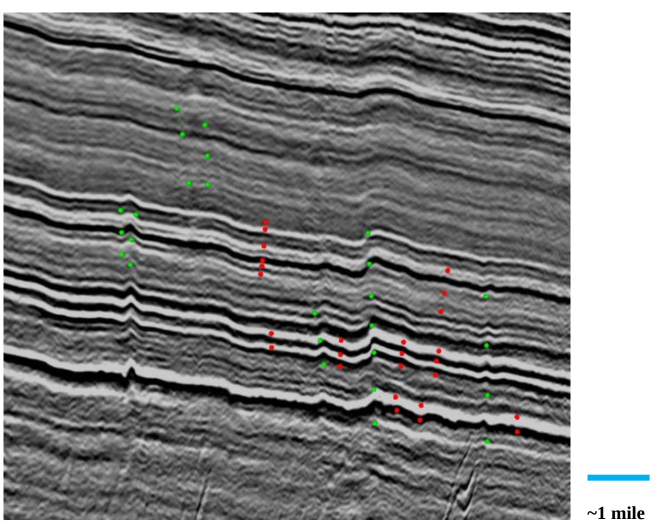

Figure 4. An example of a point set that is fed to the neural network. Green points refer to fault locations. Red points refer to non-fault locations.

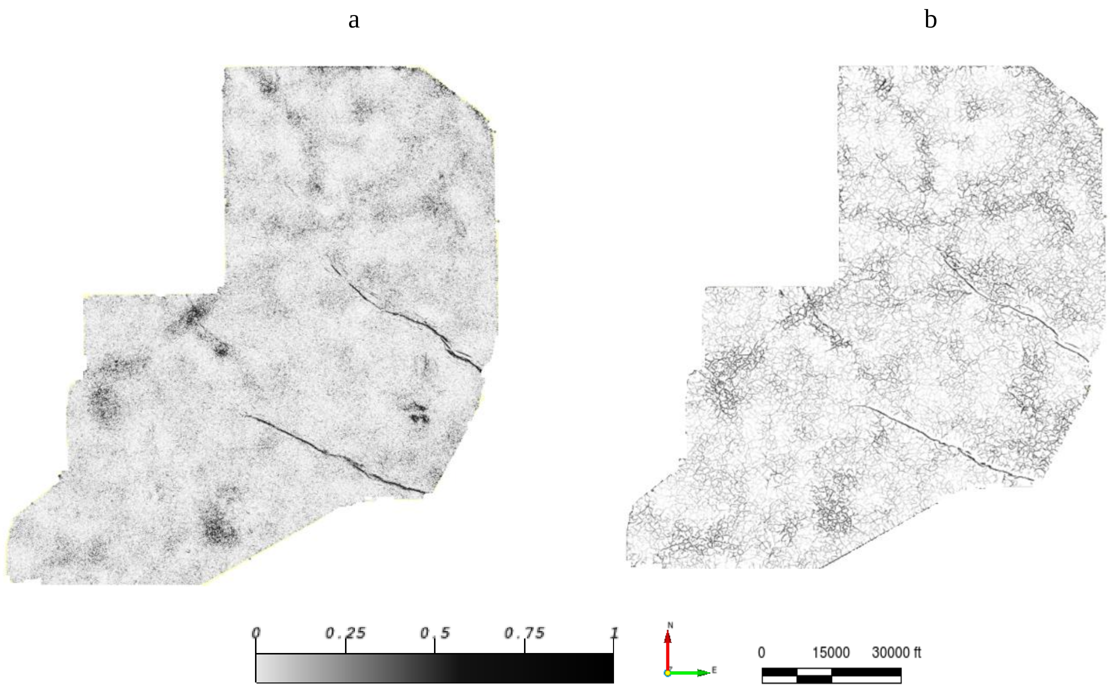

Figure 5. a) The distribution of faults and fractures predicted by machine learning displayed on Utica shale horizon. b) Neural network results using thinned fault likelihood attribute.

Case study 2

The second case study focuses on a 3D seismic volume from the Kerry field, located offshore south-eastern Taranaki basin, New Zealand. The Taranaki basin, Late Cretaceous-Cenozoic, is an offshore basin situated along the western margin of the North Island. The Taranaki basin eastern margin is delineated by a basement high (King and Thrasher, 1996). The movement of Taranaki basin and Cape Egmont faults were responsible for the structural development of the basin. By Early Miocene, the basin experienced a tectonic regime change from extension to compression (Palmer and Bulte, 1991). The aim of this study is to analyze and understand the structural pattern particularly the faults and the fractures in the 3D seismic data. For this purpose, we used machine learning to predict the discontinuities. Seismic data was enhanced using a dip steered median filter to better visualize the faults and the fractures prior to the use of the ANN (Figure 2c and 2d). Attributes that are designed to highlight seismic discontinuity are used. Once neural network is trained, we applied the single output attribute that represents the fault probability to the entire data set. Final results are displayed on a horizon attribute map as in

Figure 6. Based on the visual analysis of the structural pattern of the faults, most of the faults have a NE-SW trend. The faults in the northern and southern side as indicated by red arrows seem to have straight line style. While the faults in the middle as indicated by green arrows, tend to have a curving signature. This might be due to different tectonic regimes that affected the Taranaki basin during Early Miocene. The confusion plot in figure 7 shows how well this model performs. The misclassification rate was low which indicates the accuracy of the faults prediction as shown on the horizon attribute map.

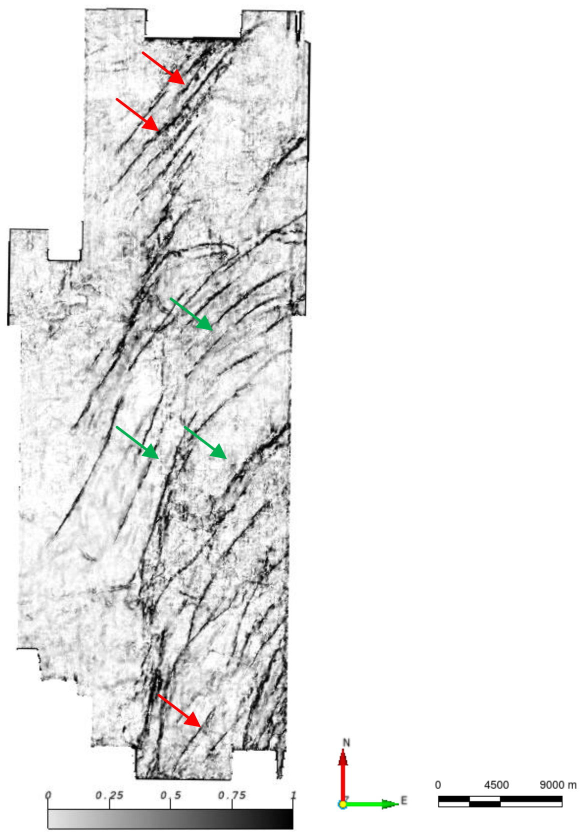

Figure 6. Neural network fault prediction results displayed on a time slice horizon.

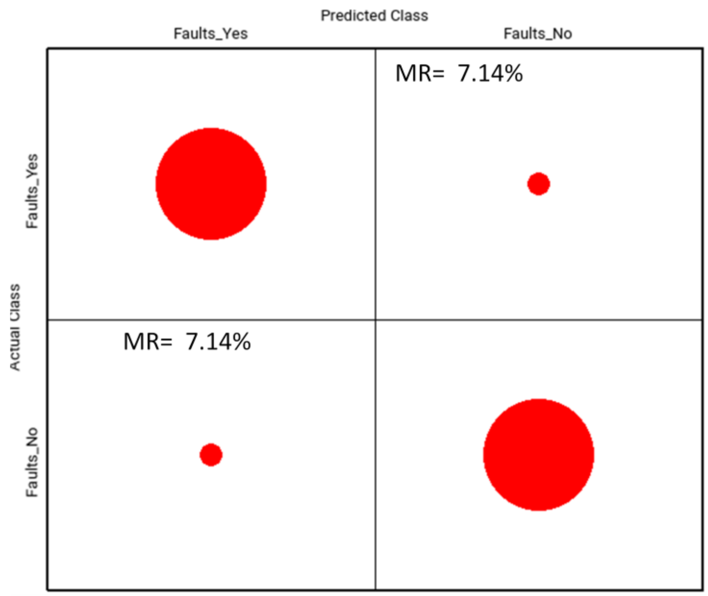

Figure 7. The confusion plot displays how well the neural network predicted the object of investigation. Misclassification rate is as low as 7.14%, which indicates the training and test data set that is being classified in the wrong class.

Conclusion

Machine learning is proven as an effective tool in predicting geological objects in seismic data. In this paper, we applied ANN supervised learning approach on two different data sets aiming to improve the prediction seismic discontinuity in 3D seismic volume. The quality of neural network final results is directly related to the relevant information extracted from seismic attributes. A typical machine learning workflow was applied, including attribute extraction, training, testing, and applying the neural network on the entire seismic data set. Such workflow allows us to generate models with high accuracy. Machine learning prediction of fault location and fractures density demonstrates its ability to provide outstanding outcomes. Neural network applied on the Utica shale horizon revealed significant detail of faults and fractures. Normal faults in Kerry field 3D data set, Taranaki basin, were nicely mapped and interpreted.

Acknowledgments

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