FAULT INTERPRETATION USING NEURAL NETWORKS

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Keywords

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Summary

Fault detection is essential for reservoir characterization. Though many tools have been developed in the past decades, automation of this task remains a challenge. We propose the application of Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN) to seismic fault detection. DNN and CNN both are deep learning methods that have extensive applications in the computer vision community because it is highly efficient in object detection. For the algorithm to perform well, we need to provide a large number of data of fault and non-fault for training, which is not readily available. To this end, we take synthetic data for training and a mixture of synthetic data and real data for testing. The input of our network is the seismic amplitude only; the method does not require computing any seismic attribute. We apply a strategy of 10x10 cross-section classification along with the images. Our network shows that CNN performs better when tested on some real data.

Introduction

Faults are typically imaged as discontinuity in the data. Faults are critical components of many subsurface hydrocarbon traps. For many years, faults were interpreted by visual recognition of discontinuities in the seismic data, which were then manually interpreted as fault cuts on seismic sections. To check how accurate, the fault surface interpretation is done by the interpreters, trap integrity, volumetric and reservoir compartmentalization are analyzed. Various techniques, methods and algorithms are presented which better interprets and defines the fault surface geometry in past several years. Due to the optimization of the methods and the tools to detect and extract fault data, it has become very easy for the geologists to interpret large seismic sections. The typical fault is shown in Fig. 1.

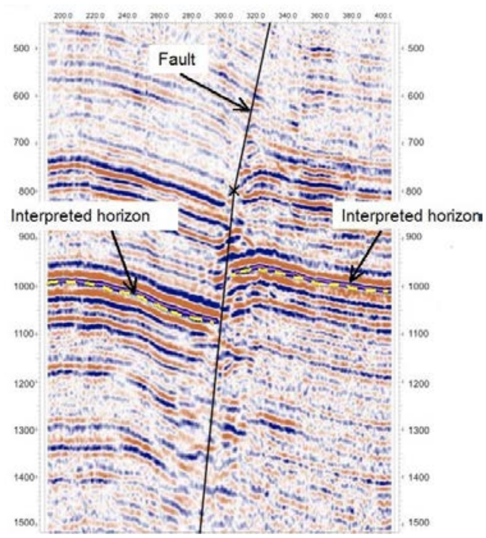

Figure 1: A typical seismic fault.

Faults are classified according to the direction of relative movement along the fault. The faults are categorized as normal fault, reverse/thrust fault, strike slip fault and listric fault. The terms hanging wall and foot wall denoted in Fig. 2 refer to the position of the plates after movement.

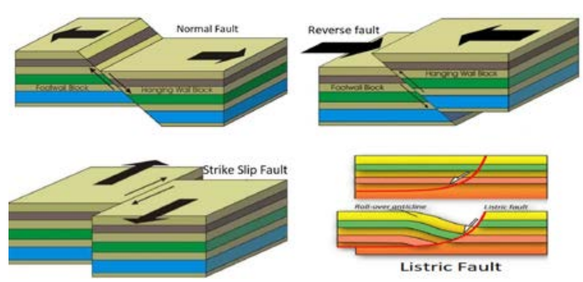

Figure 2: Fault classification.

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The fault detection is very necessary for identifying reservoir regions. Phase of the life cycle of the reservoir is related to objective of the fault interpretation. If the detailed knowledge of the fault system regarding the location of the well is provided, then flow in the reservoir can be optimized. Automatic detection and extraction of faults from fault surfaces is done using fault enhancing attributes such as semblance, variance, Eigen structure or gradient structure tensor. Enhancement of the faults denotes enhancement of the discontinuities in the seismic dataset.

The seismic attribute can be used as input to the training dataset. It has its pros and cons, and along with enhancing fault, it may enhance some other artifacts also. Seismic attributes usually require massive computation, and, alone, are not sufficient for efficient fault identification. For that, a human interpreter must spend time finalizing the study manually. In many cases, in order to extract fault location automatically, the attributes are post-processed. For example, [Gibson et al, 2005] use semblance to get high probable fault points and then later join them to get the fault surface; [Zhang et al, 2014] apply a skeletonization on the coherence cube to extract fault lines; and [Wang and AlRegib, 2014] [Wang and AlRegib, 2017] use the Hough Transform to extract fault locations from binarized continuity maps.

Another approach is to combine multiple attributes. The work of [Tingdahl and de Rooij, 2005] uses a neural network to combine a set of 12 attributes and generate a fault probability map. Recently, [Di et al, 2017] combined 14 attributes in a multi-attribute Support Vector Machine. A simple deep neural network (DNN) can also be used for finding faults. DNN training is done to learn a relationship that maps the data space to spatial points, which indicate the presence of faults [Mauricio, 2017].

In this work, we train CNN and DNN with synthetic data and try to apply the classifiers on real data to study the generalizability of the model. Making a proper and general classifier is a challenging task that will save the computation cost of training and testing the networks for every dataset. CNNs combine a few steps of convolution with a fully connected neural network to perform classification, whereas DNN is a neural network having deep layers. CNN and DNN recently proved to be powerful in various computer vision tasks ([Rawat and Wang, 2017], [Zhiqiang and Jun 2017]), among which seismic objects detection ([Waldeland and Solberg, 2017], [Di et al, 2018], [Huang et al, 2017]). Synthetic data present a great advantage to provide total control on the ground truth and are easily scalable in terms of the number of inputs as compared to that of real data. Our input is the seismic amplitude only, and our method does not require any prior seismic attribute computation. We use a 10x10 cross-section classification scheme on synthetic data for network training.

Method

First, we generate synthetic seismic images where we control the location of the faults. Second, we extract Fault and Non-fault cross-sections from the synthetic seismic data. Then, we train the data using DNN and CNN. For testing, a testing set is prepared, which contains both synthetic and real data.

For synthetic dataset generation, we followed the process given by [Hale, 2014]. First, a reflectivity model is created randomly. Then extending along the section, image transforms create sequential rock deformations along time.

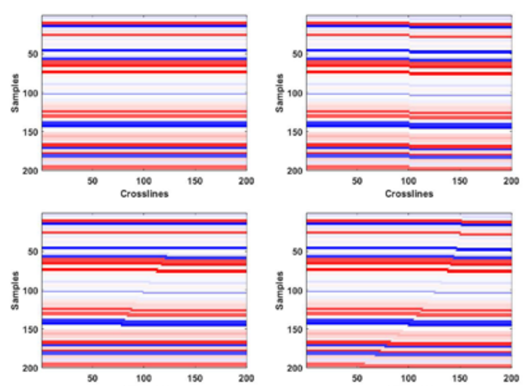

Figure 3: A synthetic seismic data and the three different types of fault created.

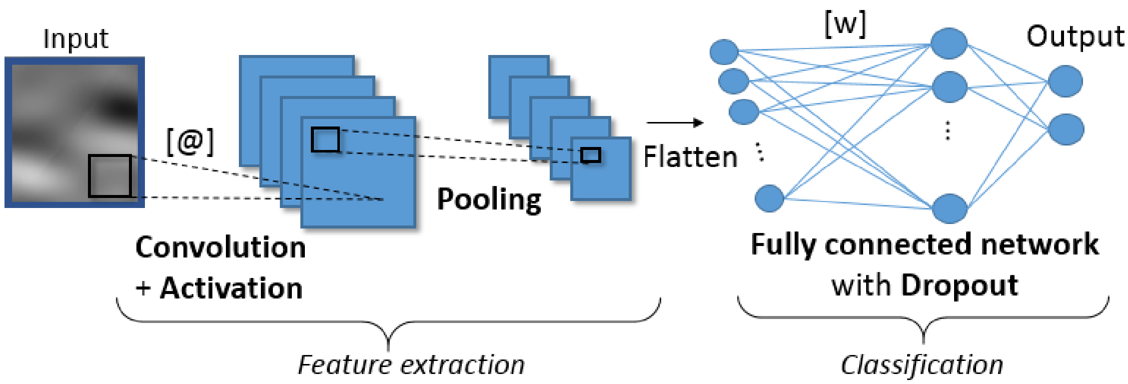

Figure 4: Standard architecture of a CNN network, number of convolution layers and pooling layers can be varied as per the requirement and [@] = trainable filters; [w] = trainable weights Flatten operation converts the 2D list of matrices into a 1D list of neurons.

Finally, it is convolved with a Ricker wavelet. We created three types of fault that are straight, slant, and curved. Fig. 3 illustrates the synthetic data and the faults created.

For applying machine learning techniques, we will have to give the features of data as input. In the case of seismic data, seismic attributes will be required. However, for CNN, the advantage is that seismic attribute input will not be required. The neural network will find the best possible feature on its own. The fault points are one kind of discontinuities, and it will cause the neighborhood attributes will differ. So the seismic amplitudes of the neighborhood are fed as input to the network. 10x10 cross-sections are created for the same. Fig 5 shows

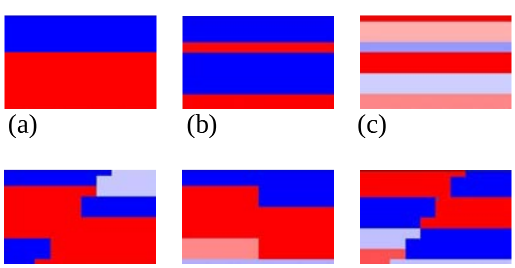

Figure 5: (a), (b), and (c) show small cross-section that are non-fault and (d), (e), and (f) show small cross-sections that are fault.

examples of such cross-sections having fault and no-fault. Ten thousand such cross-sections are created for both fault and non-fault data-set. These are the inputs for the training of the networks.

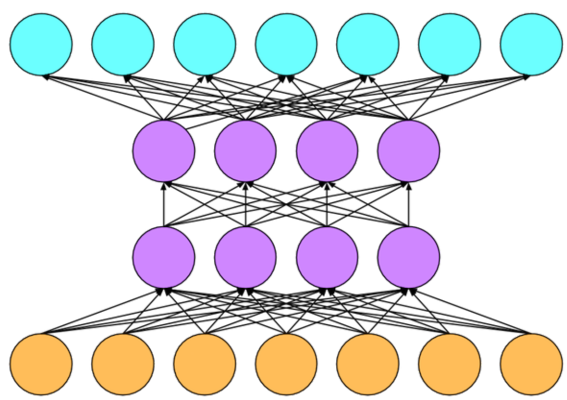

Figure 6: A typical architecture of a DNN, below layer is the input layer and the top one is the output layer, middle layers are the hidden layers.

Figure 6 shows the architecture of a DNN; the input layer takes the input of seismic amplitudes. The activation for hidden layers and the input layer used is a rectified linear unit (Relu), and for the output layer, softmax activation is used. Two hidden layers are used for the network. Figure 5 shows the standard CNN architecture used. For the training of this network first one convolution layer is used, and then pooling is done followed by another convolution layer. Drop out regularization is used, and stochastic gradient descent is used for optimization. Relu activation is used for all layers except for the output layer, and softmax activation is used for the output layer. 3x3 kernel was used for both the convolutional layers.

Results

After training on the given networks, the network was tested on a test set. The test set contains two thousand cross-sections, out of which 1500 are synthetic data, and 500 are real data. The DNN architecture gave an accuracy of 41%, whereas CNN architecture gave an accuracy of 86%. CNN gave better results because the convolution could map the proper relationship between the seismic amplitude cross-sections and the fault features.

Conclusion

This paper presented a methodology for the detection and segmentation of faults in seismic images, using a CNN based approach for training and classification. The use of CNN allowed us to train with the seismic amplitude map as the only input feature: explicit feature extraction and selection steps were unnecessary. However, we highlighted the large number of empirical parameters used in CNNs, which makes model fine-tuning difficult.

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