ASSISTED FAULT INTERPRETATION BY MULTI-SCALE DILATED CONVOLUTIONAL NEURAL NETWORK

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Summary

Assisted fault interpretation leveraging machine learning techniques has become a promising way to identify faults in seismic. In geophysical exploration, faults are often considered as a sealing surface which traps hydrocarbons and forms reservoir zones. Thus, correctly identifying fault locations is critical. Fault identification can be treated as a semantic segmentation issue where we classify each seismic pixel into one of a given set of categories, such as fault or non-fault. To be successful we need to combine pixel-level accuracy with global-level feature identification. In this abstract, we propose a novel deep learning network with multi-scale dilated convolution to identify fault locations. It is based on adaptions of a convolutional neural network architecture which has been used for image classification and semantic segmentation. The motivation is that dilated convolution supports exponentially expanding receptive fields without losing resolution or coverage. We implemented multiple dilated convolution layers with variable dilation rates to systematically aggregate multi-scale seismic information. Several tests are shown and demonstrate the improvement of identification accuracy with higher resolution.

Assisted Fault Interpretation by Multi-scale Dilated Convolutional Neural Network

Introduction

In geophysical exploration, faults are often considered as a sealing surface to trap hydrocarbons and form reservoir zones. Thus, correctly identifying fault locations is critical. Assisted fault interpretation leveraging machine learning techniques has become a promising way to predict fault locations. Fault prediction can be treated as a semantic segmentation issue where we classify each pixel into one of a given set of categories, such as fault or non-fault. To be successful we need to combine pixel-level accuracy with global-level feature identification. Among different semantic segmentation algorithms, a convolutional neural network (CNN) has been demonstrated as a successful architecture to extract fault patterns from seismic data. However, different levels of signal-to-noise ratio in seismic data and other artifacts can degrade prediction accuracy, which can result in low resolution which prevents identifying the faults.

A deep learning-based fault identification process can quickly provide an estimate of fault location in seismic data. Wu et al. (2018) performed an efficient image-to-image fault segmentation by using a supervised, fully convolutional neural network. They created multiple synthetic seismic images and corresponding binary fault labelled images to train a fault segmentation network. Jiang and Norlund (2020) proposed a workflow to rank different seismic attributes for predicting faults, then selected the most important attributes to assist a multi-channel CNN and improve the continuity of imaged fault segments. To improve the resolution, Fisher et al. (2015) proposed an approach to improve the segmentation resolution by repeating up-convolutions to recover lost resolution while carrying over the global perspective from down-sampled layers. Simonyan and Zisserman (2015) integrated multi-scale contextual information via successive pooling and subsampling layers that reduced resolution until a global prediction was obtained.

In this abstract, we proposed an innovative deep learning network with multi-scale dilated convolution for fault prediction. It is based on adaptions of CNN architecture which have been used for image classification and semantic segmentation. The motivation is that dilated convolution supports exponentially expanding receptive fields without losing resolution or coverage. We implemented multiple dilated convolution layers to systematically aggregate multi-scale seismic information. We have demonstrated our approach in synthetic data and field data to exhibit the improvement of prediction results with higher resolution.

Methods

Many geophysical interpretation problems are instances of dense prediction, which describes a discrete or continuous label for each pixel in the image and requires classifying each pixel into one of a given set of categories (e.g. classification as fault, salt, or horizon). In computer vision, researchers have been trying to implement different neural networks to obtain images by multi-scale dense prediction (e.g., Liu and He, 2015; Yu and Koltum, 2016) for various applications, such as to train a model in an autonomous car. Compared with standard convolution, dilated convolution has shown the ability to detect finer details by bringing a broader view of the input to capture more neighbouring information. In 1D, dilated convolution is defined as:

$$output[i] = \sum_{l=1}^{L} input[i + r * l] * h[l]$$

Where $input$ and $output$ are extracted seismic features in a CNN. $h[l]$ represents the convolution filter of length L, and r denotes the dilation rate we use to sample $input[i]$. A standard convolution will have a dilation rate equal to 1. We then combine standard convolution and dilated convolution in a 3D CNN, followed by a multi-scale aggregated module, to calculate a full range of seismic receptive fields. Our multi-scale module (Table 1) is based on a rectangular prism of a set of dilated convolutional layers, which support the exponential expansion of the receptive field without losing resolution or coverage. This module takes the feature maps produced from the previous layer as input and outputs the same form of the feature maps. Since the input and output have the same form, it is convenient to plug the multi-scale module into other existing fault prediction networks.

Table 1: A multi-scale dilated convolution module

Layer	1	2	3	4	5	6	7
Convolutional kernel	3x3	3x3	3x3	3x3	3x3	3x3	Add Layer 1 to 6
Dilation factor	1	2	4	8	16	32	

Figure 1 illustrates the multi-scale aggregated receptive fields with dilation rates 1, 2, and 4. In this form, we applied the same convolutional kernel (3x3x3) to each layer, therefore each layer will have the same channel and could be used to directly obtain a result of dense classification. We then consider the output as the input of the next layer, until the 6th layer is completed. The 7th layer will stack the feature maps from Layer 1 to Layer 6. Since we pass the feature channels through multiple layers which expose different scaled seismic information, it can be used to increase the resolution of the feature maps.

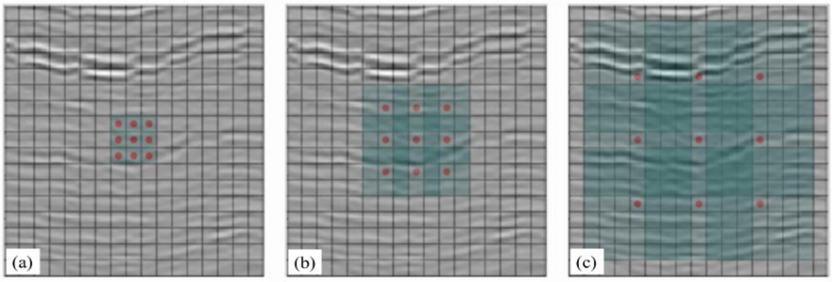

Figure 1*: Illustration of dilated convolution through seismic data. Subsequent convolutional layers have dilation rates of L= 1 (a), 2 (b), and 4 (c), respectively. (a) The result is produced by 1-dilated convolution, each element has a receptive field of 3x3x3. This is the same with standard convolution; (b) The result is produced from (a) by 2-dilated convolution; (c) The result is produced from (b) by a 4-dilated convolution.*

Figure 2 shows our CNN with a multi-scale dilated convolution module. The input seismic data will be fed into the standard convolutional layers with different filters to extract the different levels of feature maps. It will then go through a multi-scale dilated module, and then perform up-sampling to recover the position of each extracted feature.

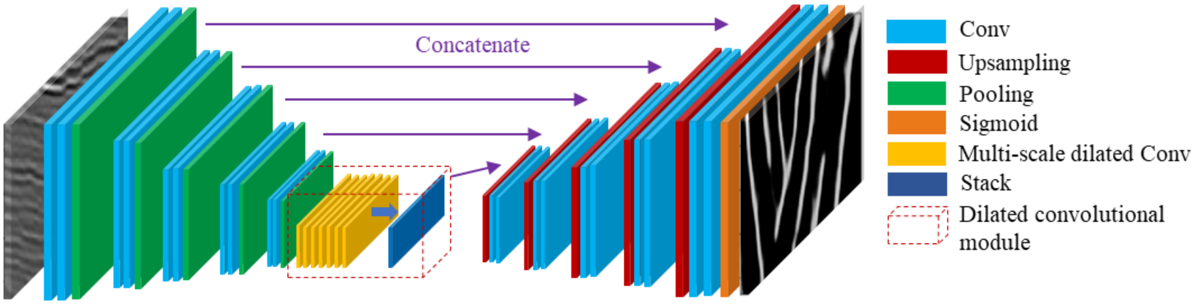

Figure 2*: Our CNN architecture with a multi-scale dilated convolution module.*

Examples

A data generator was implemented to create synthetic fault planes to be used as training data to feed into the standard CNN and the multi-scale dilated CNN. Besides the multi-scale dilated module, the remaining network layers were kept the same between the two models to avoid any discrepancy during training. We implemented the training workflow in TensorFlow libraries and leveraged a multi-GPU architecture to expedite the training process. Figure 3 shows the training loss and accuracy. At each epoch, the multi-scale dilated CNN obtained a lower loss rate and higher accuracy than the standard

CNN. The best accuracy during training from the standard CNN was 0.9686 whilst from the multi-scale dilated CNN it was 0.9758. Figure 4 shows a validation test from synthetic data. In this test, the accuracy of standard CNN is 0.915 whilst the accuracy of multi-scale dilated CNN is 0.934. The prediction result from multi-scale dilated CNN shows better prediction on two near faults and brings a clearer image at the fault intersections.

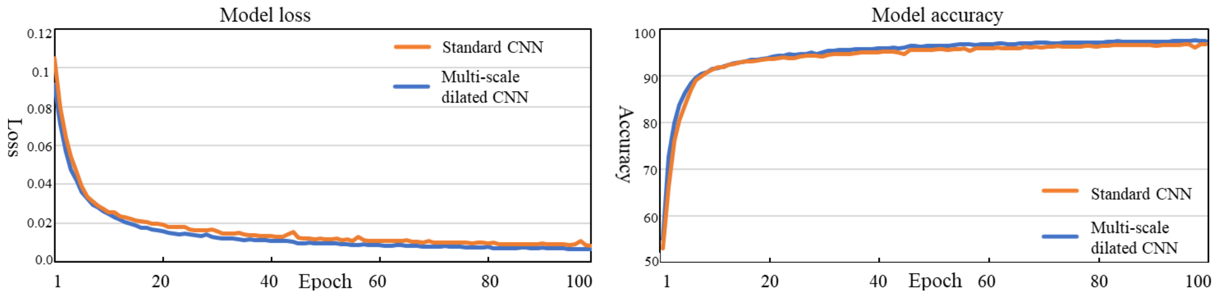

***Figure 3**: Model loss and accuracy comparison between standard CNN and multi-scale dilated CNN. At epoch 100, the model loss for standard CNN is 0.0083 whilst for multi-scale dilated CNN it is 0.0064. Model accuracy for standard CNN is 0.9686 whilst for the multi-scale dilated CNN it is 0.9758.*

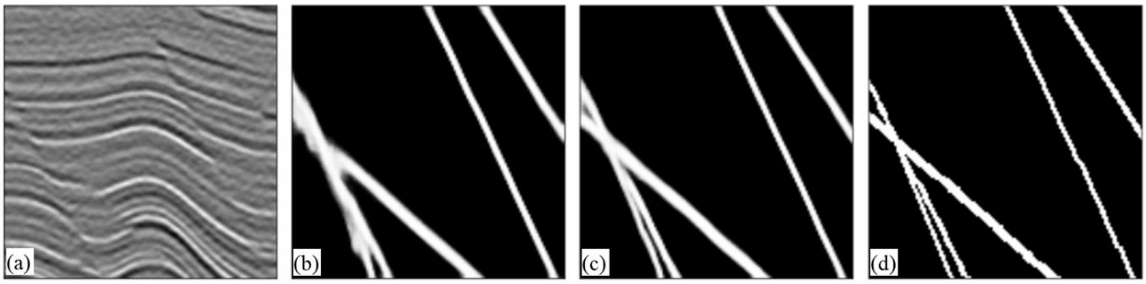

***Figure 4**: A synthetic data test. (a) Seismic data; (b) Fault prediction by standard CNN; (c) Fault prediction by multi-scale dilated CNN; (d) The ground truth. Both CNNs performed well to predict faults where a simple structure exists, but the multi-scale dilated CNN predicted finer details which separated two closely spaced faults, and also showed a higher resolution at fault intersections.*

Figures 5 and 6 show section and time slice comparisons for fault prediction from the Kerry3D dataset provided by New Zealand Petroleum and Minerals. Figure 5a used a standard CNN trained model to predict the fault probability map, and Figure 5b used a multi-scale dilated CNN trained model to predict the fault probability map. It was observed that the fault segment predicted by multi-scale dilated CNN demonstrates improvement in the continuity of the fault segments and also reveals some missing fault segments. Figure 6 shows a time slice comparison on the same dataset at t = 0.5 sec. The multi-scale dilated CNN model (Figure 6b) predicts fault segments with higher resolution whilst mitigating acquisition footprints observed in Figure 6a.

Conclusions

For this abstract, a novel multi-scale dilated CNN architecture was implemented to help improve the prediction accuracy of fault probability maps. In this multi-scale module, the input feature maps and output feature maps have the same form, therefore it is convenient to plug this multi-scale dilated module into other existing fault prediction networks. We have demonstrated that multi-scale dilated CNN is capable of improving the continuity of fault segments with higher resolution as well as mitigating acquisition artifacts. The improved fault images make it easier to extract discrete fauslt planes as part of the complete seismic interpretation workflow.

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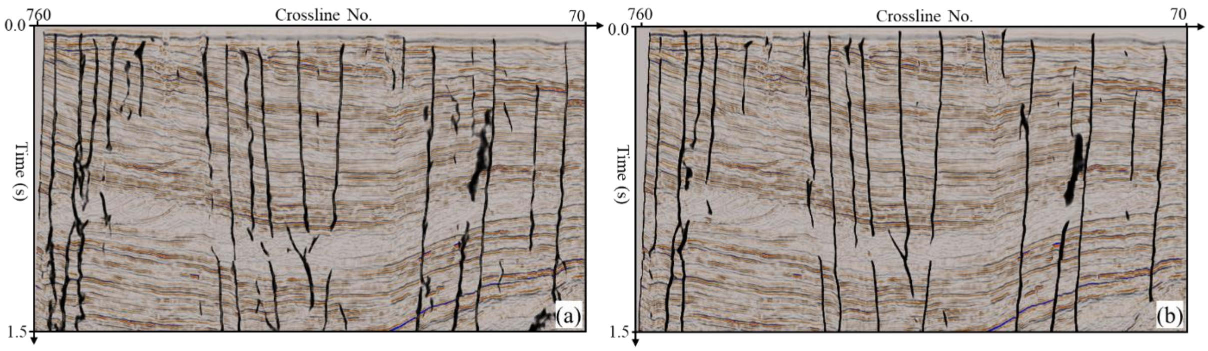

Figure 5*: The prediction comparison along the inline direction between (a) Standard CNN trained model and (b) Multi-scale dilated CNN trained model.*

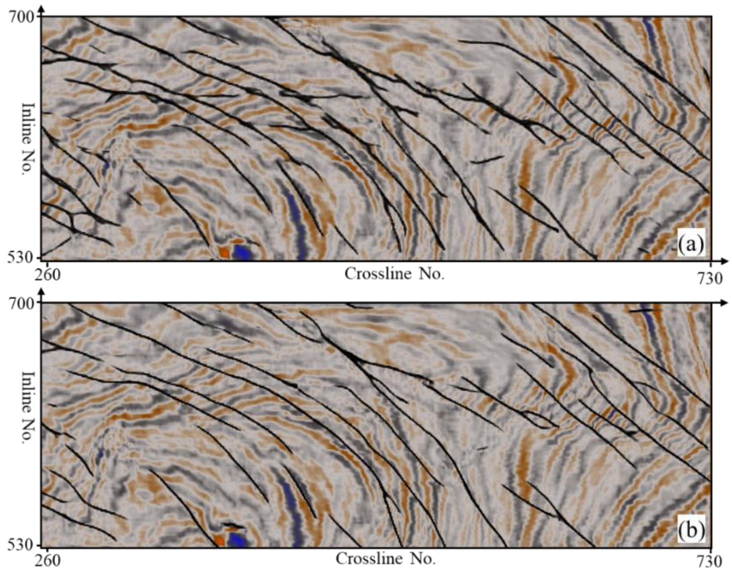

Figure 6*: The prediction comparison on time slice t=0.5sec between (a) The standard CNN trained model and (b) The multi-scale dilated CNN trained model.*