Semantic segmentation for seismic facies classification - Computer Vision

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Abstract

The seismic facies classification is an essential procedure in exploration seismology as well as reservoir characterization. In general, the manual facies classification is a time-consuming task because it requires visual examination of a large volume of 3D seismic image. I suggest to adopt a convolutional neural network to automate the classification task. 3D seismic data and corresponding manual analysis results are used for training the networks. Also, I will introduce a novel data augmentation method. The test result shows that the trained model perform reasonably.

1 Introduction

The seismic facies classification is an essential procedure in reservoir characterization, which is a fundamental and important step in hydrocarbon exploration. It aims to interpret the subsurface as its facies. Experts perform it by considering various things such as the lateral continuity, seismic amplitude, and interval velocity from the seismic data. Traditionally, a group including geophysicists, geologists, and petrophysicists classify a 3D seismic data manually. In general, the manual facies classification is a time-consuming task because it requires visual examination of a large volume of 3D seismic image. In addition, the results are highly subjective and rely on the processor's experience.

In this report, I propose to adopt Convolutional Neural Networks (CNN) to perform the facies classification automatically. Specifically, I adopt supervised learning for a semantic segmentation approach. Note that this is a public project provided by SEG Advanced Modeling.

2 Related work

The CNN have been adopted for various seismic applications, but only few attempts are performed for the facies classification. One used a patch-based encoder-decoder networks [1]. Also, GAN was used for the task [2].

3 Dataset

A 3D seismic image from a field data called "Parihaka," provided by the New Zealand government, is given in terms of a dataset. The label is interpreted by expert geologists that included a total of six different facies (Figure 1). The total size of ataset are: (1006 x 590 x 782) for training and (1006 x 841 x 334) for testing.

CS230: Deep Learning, Winter 2018, Stanford University, CA. (LateX template borrowed from NIPS 2017.)

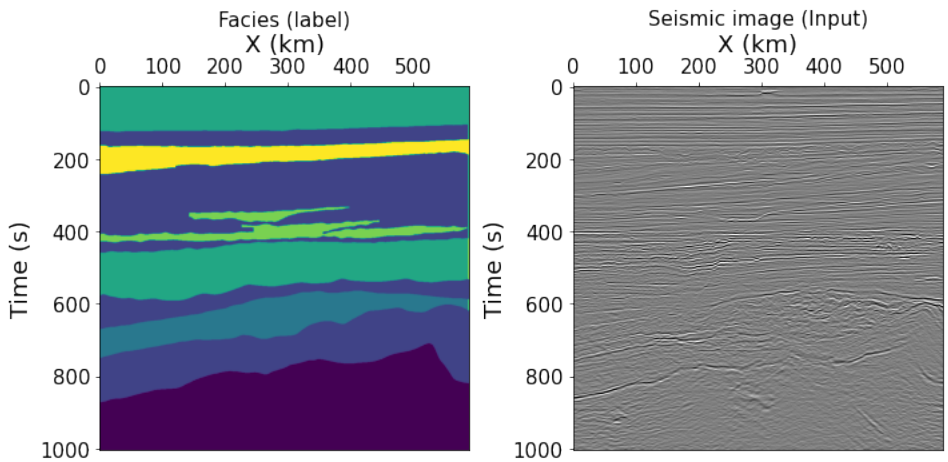

Figure 1: (left) Seismic facies interpreted by an expert and (right) corresponding seismic image are shown.

4 Methods

As mentioned earlier, my approach is the CNN based semantic segmentation. In terms of network architecture, I adopt the DeepLabV3 [2] with ResNet101. One of the most crucial issues of this project is that the given training data suffers an imbalanced label. Regarding this issue, I assigned different weights to each class during the update. Weights are depending on the number of each class. The other issue is overfitting. As the given training data has limited features, I need to perform the data augmentation. I perform the flipping of both the input and the label. In addition, I augment the data by taking the 2D sliced from the two different axes (X, Y). Finally, I adopt the 3D random elastic deformation [4] for the data augmentation (Figure 3) In general, these augmentation helps to avoid overfitting as well as improve the stability of the result.

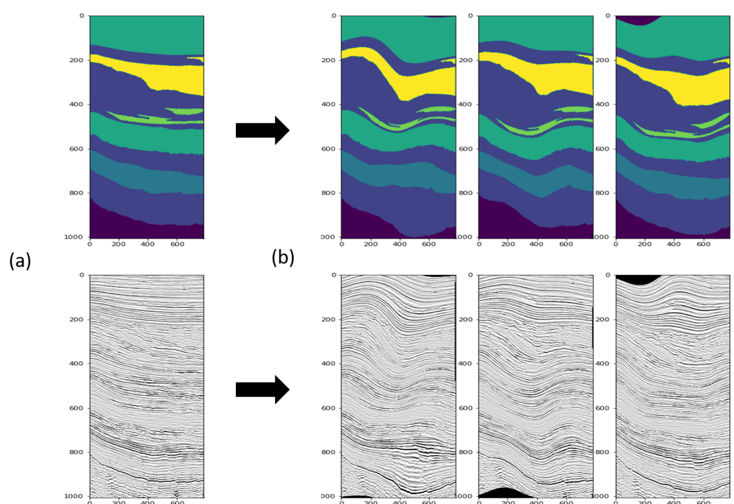

Figure 2: Original data (a) with 3D data augmentation results (b) with random elastic deformation [4].

5 Results

I tested three cases: Encoder-decoder networks (no augmenated data), DeepLabv3 [5] networks (no augmenated data), and DeepLabv3 networks (augmenated data). The results show that the last one provided the best result in terms of the stability and the accuracy. Note that, the SEAM AI [3] doesn't provide the label for the test data yet. So, visual comparison is the only way to compare.

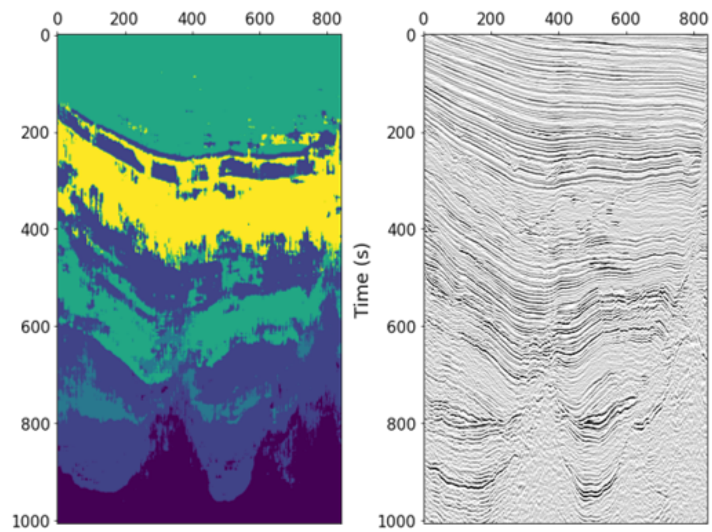

Figure 3: Encoder-Decoder networks result (left) with its input (right)

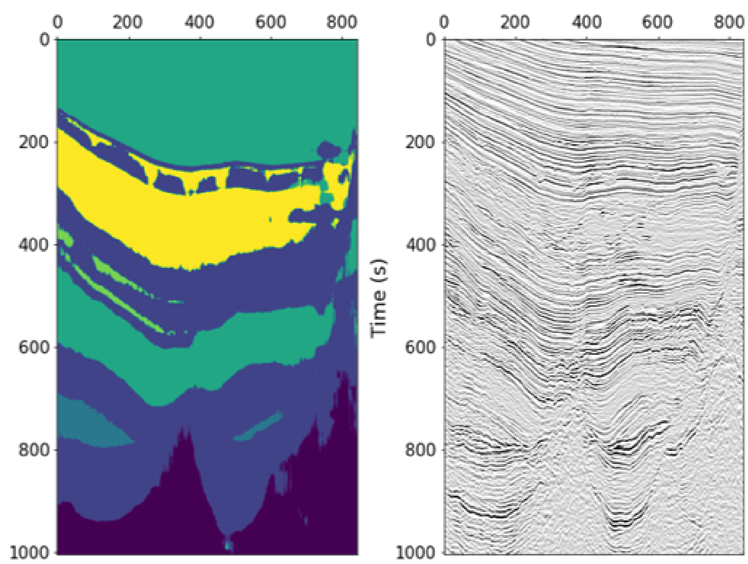

Figure 4: DeepLab v3 networks result (left) with its input (right)

6 Conclusions

In this project, I suggest adopting CNNs to perform the seismic facies classification automatically. Original training data was augmented by the flipping and the random elastic deformation. Overall, the results are satisfactory since the trained model can classify the facies reasonably. However, I still can see some area has high uncertainty. Adopting 3D CNN could be a solution. Post-processing, the result can be another solution. As this project is still on-going, I will conduct these as my future works.

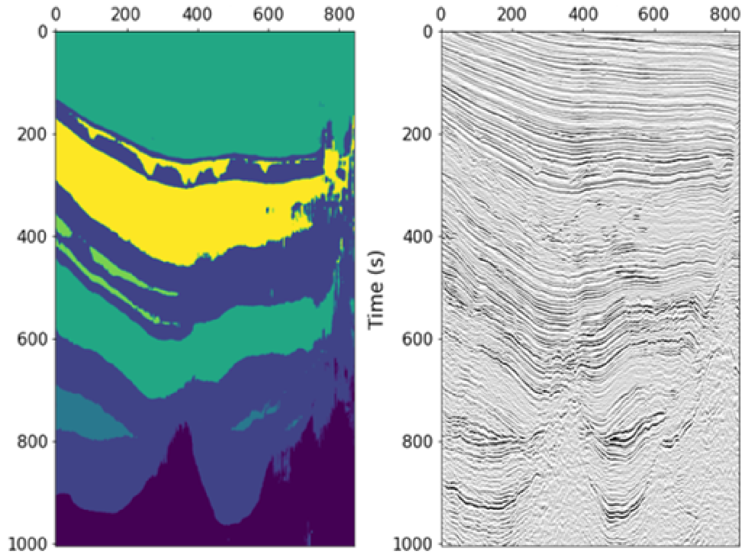

Figure 5: DeepLab v3 networks with augmented training data result (left) with its input (right)

References

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[4] Pérez-García, Fernando, Rachel Sparks, and Sebastien Ourselin. "TorchIO: a Python library for efficient loading, preprocessing, augmentation and patch-based sampling of medical images in deep learning." arXiv preprint arXiv:2003.04696 (2020).

[5] Chen, Liang-Chieh, et al. "Rethinking atrous convolution for semantic image segmentation." arXiv preprint arXiv:1706.05587 (2017).