Seismic stratigraphy interpretation via deep convolutional neural networks
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Summary

Depicting geologic sequences from three-dimensional seismic surveying is of wide applications to subsurface reservoir exploration. In this paper, we present an innovative workflow for seismic stratigraphy interpretation by utilizing the state-of-the-art deep convolutional neural networks (CNNs). Specifically, the workflow consists with two components: (a) seismic feature self-learning (SFSL) and (b) stratigraphy model building (SMB), each of which is achieved in a deep CNN. While the latter is supervised and of the typical network architecture used in image segmentation, we design the former as unsupervised and requiring no knowledge from domain experts. Compared to the convolutional approaches, the proposed workflow is superior in two aspects. First, by initializing the SMB network from the SFSL one, it successfully inherits the prior-knowledge for understanding the target seismic data, and therefore such supervised learning can be efficiently completed by only a small amount of training data. Second, for the conveniences of seismic experts in providing training labels, we design our workflow applicable to three scenarios, trace-wise, paint-brush, and full-section annotation. The performance of our proposed workflow is verified through application to two real seismic datasets from the North Sea and the Solsikke. It is concluded that the new workflow is not only capable of providing reliable seismic stratigraphy interpretation but holds the potential for assisting other geophysical problems, such as geobody detection.

Introduction

Seismic stratigraphy interpretation aims at depicting the subsurface geologic sequences from three-dimensional (3D) seismic surveying and thus is essential to the success of reservoir exploration. For achieving such a goal, one of the conventional workflows is the integration of horizon tracking and geologic modeling. Specifically, the step of horizon tracking aims at interpreting the seismic reflectors, and following the fundamental geologic rules (e.g., no horizon crossing). Apparent, the accuracy of horizon tracking determines the quality of such a workflow, and therefore such supervised learning can be efficiently completed by only a small amount of training data. Second, and more importantly, the convolutional CNNs require training data to be fully labeled, which works effectively for reflections with strong amplitude, high signal-to-noise ratio (S/N), and high degree of lateral continuity. Otherwise, when performed on a low-quality horizon, the conventional seeded horizon tracking is highly prone to making mis-interpretation.

The recent success of machine learning, particularly convolutional neural network (CNN) in image processing (e.g., Zeiler et al., 2011; Long et al., 2015, Ronneberger et al., 2015; Kallenberg et al., 2016; Badrinarayanan et al., 2017) has brought new insights and tools into the vision of seismic interpreters, and enormous efforts have been made in utilizing the deep CNNs for resolving the typical seismic interpretation problems, such as saltbody delineation and fault detection (e.g., Huang et al., 2017; Di et al., 2018b; Wu et al., 2018; Xiong et al., 2018; Zhao and Mukhopadhyay, 2018). To the best of our knowledge, however, litter work has been done towards CNN-assisted seismic stratigraphy interpretation. It appears straightforward for simply extending the CNNs from fault/salt to stratigraphy. However, we notice two major limitations for it. First, it often requires a large amount of training data to build a reliable interpretation machine, which is not available in seismic interpretation domain and requires plenty of efforts and labors from an experienced interpreter. Otherwise, over-fitting would occur that limits the CNN performance on the training data only. Second and more importantly, the convolutional CNNs require training data to be fully labeled, which is not always feasible in the seismic domain due to the interpretational uncertainties. Commonly, with the quality of seismic signals decreasing from shallow to deep areas, the seismic interpreters become less confident in providing correct annotations.

For addressing both limitations, this study presents an innovative workflow for automatic seismic stratigraphy interpretation through deep convolutional neural networks (CNNs).
StratML via deep CNNs

interpretation through deep CNNs, which consists with two steps: seismic feature self-learning and stratigraphic model building. Moreover for facilitating the job of training data annotation, 3 application scenarios are proposed for applying the proposed workflow. Finally, the proposed workflow is tested in all the 3 scenarios through the application to two real seismic data sets over the North Sea and the Solsikke.

Proposed workflow

Figure 1 illustrates the proposed workflow for seismic stratigraphy interpretation via deep CNNs, which consists with two steps: seismic feature self-learning (SFSL) and stratigraphy model building (SMB). Specifically, given a seismic dataset, the step of SFSL aims at understanding all the features in the seismic dataset by a deep CNN itself, which is purely unsupervised with no input from seismic interpreters. Then, in the step of SMB, a second deep-CNN is built from the SFSL CNN for learning and recognizing the target seismic stratigraphic sequences, which is supervised by domain knowledge from an expert to ensure the result accurate and reasonable in geology (Li et al., 2019)

Application scenarios

The proposed workflow can be applied in 3 scenarios, depending on how the expert knowledge is feed into training the SMB CNN. As shown in Figure 2, we propose 3 training scenarios include,

- Trace-wise annotation, in which an interpreter selects a few representative seismic traces and marks the target sequence boundaries.
- Paint-brush annotation, in which an interpreter uses a paintbrush to highlight the target seismic sequences.
- Full-section annotation, in which a few seismic sections are fully interpreted.

If comparing the 3 scenarios, the trace-wise case requires the least amount of training data and is integrable with well interpretation. On the contrary, the full-section case requires the most human labor for data preparation. The paint-brush is most flexible in term of data preparation, in which an interpreter is capable of marking any specific zones of interest in a seismic dataset. Such paint-brush annotation is considered most useful for avoiding interpreter bias in the zones of interpretational uncertainties due to low seismic quality, since it does not necessarily touch the sequence boundaries.

Results

After illustrating the proposed two-step workflow and the 3 scenarios, we then demonstrate its applications through 3 examples, each of which is corresponding to one of the 3 scenarios shown in Figure 2.

Example 1: Trace-wise scenario

In this example, we use a subset of the NH seismic dataset over the North Sea, which covers an area of 162 km² and consists of 333 inlines, 2176 crosslines, and 576 samples per trace. For applying the proposed workflow in the trace-wise scenario, 147 traces are selected and marked in a regular grid of 7 inlines by 21 crosslines, which is about 0.02% of the available seismic data. Figure 3a shows an example of how the target sequence boundaries are marked in the 7 traces in crossline #600. In this dataset, the interpretation is challenged by the major fault, which not only breaks the sequence continuity but also weakens the signal quality in the footwall block, as demonstrated in the section of inline #600 (Figure 3b).

After applying the proposed workflow, a stratigraphy cube is generated in the same size as the NH seismic survey. For the convenience of result analysis and quality control here, the corresponding sequence interpretation in the section of inline #600 are shown in Figure 3c. Clearly, given the 0.02%

Figure 2: The 3 scenarios for applying the proposed seismic stratigraphy interpretation, in which the deep CNN can be built on trace-wise (a), paint-brush (b), and full-section (c) expert annotations, respectively.
training data, the proposed workflow is capable of continuously tracking the sequences across the major fault.

**Example 2: Paint-brush scenario**

In this example, we use the same NH seismic survey. For applying the proposed workflow in the paint-brush scenario, 3 inline sections, including #485, #560, and #635, are manually marked by a paint-brush, in which 5 sequences are of the interpretational interest. Since the 3 training sections are partially annotated, the training amount is estimated as 0.05%. Figure 4 displays the paint-brush annotation and the corresponding machine prediction. Similarly, given the small amount of training data, the proposed workflow is also capable of continuously tracking the sequences across the major fault.

**Example 3: Full-section scenario**

In this example, we use the large Solsikke seismic survey, which covers an area of 744 km² with 996 inlines, 1251 crosslines, and 574 samples per trace and (Figure 5a). For applying the proposed workflow in the full-section scenario, the 6 sequence boundaries in 2 sections, including inline #3000 and crossline #4250 (denoted by the white lines in Figure 5a), are manually annotated as shown in Figure 5b, which is about 0.08% of the available signals. In addition to the 2 training sections, expert annotations are also provided for inline #2996 (denoted by the yellow line in Figure 5a), which was not used for machine training but purely verifying the performance of the proposed workflow.

Figure 5: (a) The map view of the Solsikke seismic survey as well as the locations of 2 training sections (denoted by the white lines), 1 testing section (denoted by the yellow line), and 1 prediction section (denoted by the red line). (b) The expert interpretation of the important sequence boundaries in the training section of inline #3000.

The machine prediction is shown in Figure 6, including the training section and the testing section of expert annotations as well as the prediction section of inline #2800 that is 200 inlines away from the training section. The good match between the prediction and the seismic amplitude well verifies the performance of the proposed workflow in the full-section scenario.

Figure 6: The application of the proposed workflow to the Solsikke seismic dataset in the full-section scenario. The stratigraphy cube is clipped to the training section of inline 3000, the testing section of inline 2996, and the prediction section of inline 2800. Note the good match between the seismic and the machine prediction. The expert interpretation is marked as black curves in the training and testing sections.
Why using the seismic feature self-learning

As illustrated in Figure 1, one major innovation of the proposed workflow is to build the SMB CNN from the SFSL CNN, instead of scratch. For demonstrating the associated superiorities, we use the Solsikke seismic dataset and build two SMB CNNs, one from the SFSL CNN and the other from scratch. Our observations are twofold,

First, by inheriting the prior-known knowledge of the target seismic signals that the SFSL CNN has learned itself, the training of the SMB CNN starts with a lower loss and converges faster, as shown in Figure 7.

Second and more importantly, the use of the SFSL CNN improves the accuracy of stratigraphy interpretation at far distance, where the seismic signals are more and more distinct from the training sections. However, since the SFSL CNN has already learned all the seismic sections, the associated SMB CNN also inherits such knowledge and thereby is capable of making better prediction there. Figure 8 compares the prediction by both SMB CNNs in the inline 2500 that is 500 inlines away from the training section. Apparently, even though both SMB CNNs converge well after training (Figure 16), the SFSL-based one leads to significant improvement in the far-distance prediction with much fewer mis-annotations.

Conclusions

A two-step workflow has been presented for seismic stratigraphy interpretation by building two deep convolutional neural networks (CNNs), one for seismic feature self-learning (SFSL) and the other for stratigraphy model building (SMB). Specifically, the SFSL CNN is unsupervised and thereby capable of learning all the seismic features in a given seismic dataset by itself, whereas the SMB CNN is constructed from the SFSL one, so that it successfully inherits the prior-known knowledge about the target seismic dataset and is superior in 3 aspects over the conventional approach of training a SMB CNN from scratch, including,

- A smaller amount of training data, which is about 0.01% - 0.08% as tested in this work;
- Faster network training with a lower initial loss
- Significantly improved stratigraphy interpretation at far-distance.

More innovatively, the new workflow is applicable to 3 scenarios, including the trace-wise, paint-brush, and full-section, and thereby is flexible from the perspective of training data annotation by a seismic interpreter. For example, the paint-brush scenario allows the interpreter to provide his annotation in any shape or orientation, which can help avoid the interpreter bias in the zones of interpretational uncertainties. The trace-wise scenario paves the way for integrating seismic data and well logs, in which the most reliable well information can be used for calibrating the seismic signals while making stratigraphy interpretation.

Acknowledgments

We would like to thank Surender Manral and Gayatri Farma Novenita for providing the expert annotations used in this work.
REFERENCES


