Why using CNN for seismic interpretation? An investigation
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Summary

Three-dimensional seismic interpretation plays a key role in robust hydrocarbon exploration and production of subsurface reservoirs. With the dramatic growing size of 3D seismic surveys, however, manually interpreting a seismic volume turns to be even more challenging. In recent years, artificial intelligence and machine learning techniques have been successfully applied in various disciplines, which greatly promotes its applications in the seismic domain for mimicking an experienced interpreter’s intelligence and assisting seismic interpretation in various tasks, including facies analysis and structure detection (e.g., faults and salt domes). In this study, we first apply two most popular neural network frameworks, the multi-layer perceptron (MLP) network and the convolutional neural network (CNN), to the problem of seismic salt-body delineation and compare their performance. Then, we investigate two factors that contribute to the better performance of the CNN framework in understanding seismic signals and identifying the important seismic structures. Specifically, on one hand, the CNN is capable of automatically generating a suite of features from the original seismic images, which reduces the dependency on interpreters for computing and tuning seismic attributes. On the other hand and more importantly, the CNN classification is patch based, in which local seismic reflection patterns are taken into account for defining and learning the features of the target structures. In this way, the random/coherent seismic noise and processing artifacts of distinct patterns can be effectively identified and excluded.

Introduction

Robust reservoir characterization and modeling is greatly dependent on effectively interpreting the subsurface structures of significant petroleum implications, among which faults and salt domes are of great importance in controlling hydrocarbon migration and accumulation. In the past decades, geoscientists have devoted many efforts in developing new attributes and methods for identifying both structures.

In the field of seismic attribute analysis, there exist various schemes for seismic edge detection, reflector geometry estimation, and texture analysis to help depict faults and salt domes from 3D seismic data, each of which measures the lateral changes in seismic reflection, such as amplitude and/or waveform, by using different operators. Such attributes include coherence (Bahorich and Farmer, 1995), semblance (Marfurt et al., 1998), similarity (Tingdahl and de Rooij, 2005), curvature (Roberts, 2001), flexure (Di and Gao, 2017a), GLCM (Gao, 2003; Eichkitz et al., 2013), gradient of texture (GoT) (Wang et al., 2015), seismic saliency (Drissi et al., 2008; Shafiq et al., 2016), salt likelihood (Wu, 2016), and more derivatives (e.g., Luo et al., 1996; Gersztenkorn and Marfurt, 1999; Cohen and Coifman, 2002; Di and Gao, 2014, 2017b; Wang et al., 2016; Qi and Marfurt, 2017). Meanwhile, from the perspective of identifying seismic structures by involving computer graphics and image processing techniques, (semi-)automated interpretation has become a research focus in the past decade to improve the interpretation efficiency and accuracy. The available computer-aided interpretation methods include ant tracking (Pedersen et al., 2002), normalized cuts (e.g., Lomask et al., 2007), dynamic time wrapping (Hale, 2013), the Hough transform (Wang and AlRegib, 2014), active contour models (e.g., Shafiq et al., 2015), optimal path picking (Wu, 2016), sparse representation (Ramirez et al., 2016), and more.

Figure 1: A comparison of seismic faults (left) and salt-body boundaries (right) (in black) detected by two popular neural network frameworks: the MLP network and the CNN network. Note that both structures detected by the CNN has a lower noise level and better accuracy particularly in the zones of weak reflections, which verifies the superiority of the CNN in understanding seismic signals and identifying important structures, demonstrating its great potential in assisting 3D seismic interpretation. (Figure source: Di et al., 2018a, b)
Why using CNN for seismic interpretation

However, most of methods discussed above utilize only a limited number of seismic attributes, which run the risk of introducing artifacts or misinterpretations if the selected attributes fail to well differentiate the target structures from the surrounding ones. To resolve such limitation, the recent emerging of artificial intelligence and big data analysis provides geoscientists with new tools for integrating multiple attributes into structure interpretation, including the MLP (Tingdahl and de Rooij, 2005; Zheng et al., 2014) and the support vector machine (SVM) (Di et al., 2017). Apparently, the accuracy of such multi-attribute-based classification workflows greatly depends on an experienced interpreter in selecting a suite of seismic attributes capable of distinguishing the target geologic structures from the rest ones (e.g., Barnes and Laughlin, 2002; Zhao et al., 2015). To the best of our knowledge, however, because of the complexities of subsurface geology and the presence of seismic noise, most seismic attributes cannot serve such purpose very well. More importantly, the process of attribute selection and tuning needs to be repeated from one seismic dataset to another with the study area shifting. A simple hard-copy would undesirably fail due to the commonly varying subsurface geology and associated seismic expressions from area to area.

To reduce the dependency on seismic attribute selection, a few studies (Di et al., 2018a, b; AlRegib et al., 2018) have reported the superioriy of the CNN in detecting important seismic structures from the original post-stack seismic signals over traditional multi-attribute-based workflows as shown in Figure 1. However, little work has been done on investigating the factors that contribute to the better performance of CNN. The purpose of this study is to present such a comprehensive investigation of the CNN framework using an example of seismic salt-body delineation. In this work, we use a subset (417 inlines×417 crosslines×168 samples per trace) of the synthetic 3D SEG-SEAM data set that contains a complex salt intrusive (Orristaglio, 2016).

**CNN vs. MLP**

Figure 2 illustrates the architectures of the MLP and CNN networks used in this study for delineating the salt-body boundaries from the SEAM data set. Specifically, the MLP network has an input of nine seismic attributes, including six

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**Figure 2:** Diagrams for illustrating the architectures of the MLP network (Top) and the CNN (Bottom) used in this study for comparing their performance on seismic salt-body delineation. Nine seismic attributes are fed into the MLP network, while the CNN network generates 8 and 16 features through the first and second convolutional layers, respectively. For fair comparison, both networks contain 1 fully-connected layer and adopt the same dropout probability and loss function.
GLCM attributes (contrast, dissimilarity, energy, entropy, homogeneity, and standard deviation) and three edge-detection attributes (variance, semblance, and similarity). The corresponding attribute maps are shown in Figure 3. In contrast, the CNN has 2 convolutional layers that automatically generate 8 and 16 features, respectively. For fair comparisons,

- the training dataset for both networks are generated from the same three crossline sections (#4403, #4499, #4595), in which salt-body boundaries are manually labelled.
- both networks contain 1 fully-connected layer, adopt the same dropout probability (0.5), and use cross-entropy as the loss function.

As demonstrated in Figure 1, the CNN-based method leads to better delineation of the target salt-body boundaries, particularly in the zones of weak reflections. The failure of the MLP network results from the limited resolution of the selected nine seismic attributes on identifying such boundary zones.

For addressing the concern of over-training, Figure 4 displays the 3D view of the detected salt-body surface by the CNN tool as well as the detected salt boundaries in 6 randomly-selected vertical sections that were not involved in the training process. We notice that the CNN-based classification workflow successfully detects the salt-body boundaries as thin curves, which indicates that the trained CNN is capable of first learning the target seismic structures from original post-stack seismic amplitude and then detecting the identical ones accurately from a seismic volume.

Why CNN better?

By comparing the architectures of the MLP and CNN in Figure 2, we notice that both the MLP and CNN networks are the same in using at least one fully-connected layer to build the mapping relationship between attributes and labels. However, the stages of attribute preparation in these two networks are different in two aspects. First, the CNN automatically generates a suite of attributes from convolutional layers, which are optimized through the training process. In contrast, the MLP network requires an interpreter's knowledge in selecting and calculating a set of seismic attributes as the input to the training process. Second, the CNN-based classification uses small seismic patches as input, which takes into account the local patterns of seismic signals when building the optimal mapping relationship. Figure 5 and 6 demonstrate the 1st-layer 8 and 2nd-layer 16 CNN feature maps, respectively. Note the apparent difference between them and the traditional seismic attributes (Figure 3), implying that the CNN attributes are of less physical meaning whereas the seismic attributes are more visually interpretable.
Finally, to verify the contributions of the two factors, we feed the features automatically extracted from the CNN network (Figure 5 and 6) into the same MLP network shown in Figure 2, at sample- and pattern-level, respectively. The corresponding classification results are illustrated in Figure 7. We notice that: (a) the noise robustness is significantly improved by the pattern-level classification, since the target salt boundaries commonly have strong directionality whereas the seismic noise is often randomly distributed in the cube and has distinct patterns; (b) the use of the second-layer CNN attributes leads to better performance on defining the features of the target salt-bodies, particularly in the zones of weak reflections as labeled by the white rectangle in Figure 7.

**Figure 5:** The 8 CNN attributes automatically generated from the first convolutional layer of the CNN framework in Figure 2. The corresponding convolution mask is displayed at the bottom-left corner of each attribute map. Note the apparent difference between them and traditional seismic attributes (Figure 3).

**Figure 6:** The 16 CNN attributes automatically generated from the second convolutional layer of the CNN framework in Figure 2. The corresponding convolution mask is displayed at the bottom-left corner of each attribute map. Note the apparent difference between them and traditional seismic attributes (Figure 3).

**Figure 7:** The comparison of salt-body boundary detection in the vertical section of inline #4499 by the CNN-attribute-based MLP classification at both sample- and pattern-level. Note that the salt-body boundary detection at the pattern-level are less noisy and closer to the observation in seismic images particularly in the zones of weak reflections (labeled by rectangle), which results from the use of local seismic reflection patterns while building the mapping relationship between seismic signals and the target salt-bodies.

**Conclusions**

The CNN has proven its superiority in learning and identifying important geological structures such as faults and salt domes from the original post-stack amplitude in a more efficient manner, compared to traditional multi-attribute-based classification schemes. This study has performed an investigation of the two factors that contribute to such superiority. First, the CNN automatically generates a suite of features and optimizes them during the training process. Second and more importantly, the CNN classification is patch-based that incorporates local seismic reflection patterns into building the mapping relationship between the seismic signals and the target structures.

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