Real-time seismic image interpretation via deconvolutional neural network
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Summary
Seismic interpretation is now serving as a fundamental tool for depicting subsurface geology and assisting activities in various domains, such as environmental engineering and petroleum exploration. In the past decades, a number of computer-aided tools have been developed for speeding the interpretation process and improving the interpretation accuracy. However, most of the existing interpretation techniques are designed for interpreting a certain seismic feature (e.g., faults and salt domes) in a seismic section or volume at a time; correspondingly, the rest features would be ignored. Full-feature interpretation becomes feasible with the aid of multiple classification techniques. When implemented into the seismic domain, however, the major drawback is the low efficiency particularly for a large dataset, since the classification need to be repeated at every seismic sample. To resolve such limitation, this study proposes implementing the deconvolutional neural network (DCNN) for the purpose of real-time seismic interpretation, so that all the important features in a seismic image can be identified and interpreted both accurately and simultaneously. The performance of the new DCNN tool is verified through application of segmenting the F3 seismic dataset into nine major features, including salt domes, strong reflections, steep dips, etc. Good match is observed between the results and the original seismic signals, indicating not only the capability of the proposed DCNN network in seismic image analysis but also its great potentials for real-time seismic feature interpretation of an entire volume.

Introduction
As a fundamental tool for understanding subsurface geology, three-dimensional (3D) seismic interpretation plays a crucial role in various disciplines, such as civil engineering, geohazard assessment, and energy exploration. Interpreting a seismic volume is a time-consuming and labor-intensive process and often requires mutual collaborations between geologists and geophysicists. Manual interpretation has been the most straightforward and effective approach for solving this problem, in which an interpreter visually analyzes the seismic reflection patterns, identifies the important features, and labels them by distinct marks and/or colors. However, the dramatically increasing size of 3D seismic surveying is now significantly challenging the efficiency of such manual interpretation.

For speeding the interpretation process, geophysicists have made efforts into developing a suite of computer-aided tools, such as edge detection, geometry estimation, facies analysis, object extraction, and more. However, most of these tools are designed for interpreting one or some certain features by analyzing seismic signals from different perspectives. Correspondingly, the rest features present in a seismic dataset would be undesirably ignored. For example, as the first edge-detection tool, the coherence attribute (Bahorich and Farmer, 1995) estimates the lateral similarity of seismic waveforms and thereby is effective in depicting the faults and stratigraphic features that obviously break the waveform continuity. Since its popularity, a number of variations and schemes have been developed in improving such attribute (e.g., Luo et al., 1996; Marfurt et al., 1998; Gersztenkorn and Marfurt, 1999; Cohen and Coifman, 2002; Tingdahl and de Rooij, 2005; Di and Gao, 2014; Wang et al., 2016). While clearly highlighting the major faults of apparent displacements, however, most of the edge-detection tools are less efficient for subtle structure interpretation, such as fracture characterization and facies analysis, in which the lateral variation of seismic signals is subtle and beyond the resolution of edge detectors. Detailed summaries of the edge detection can be found in Chopra (2002), Kington (2015), and Di and Gao (2017a). For the purpose of detecting the small-scale structures, such as subtle faults and fractures, geophysicists turn to evaluating the variation of the geometry of seismic reflectors, which successfully link the fractures with the high-order reflector geometric attributes, such as curvature (Roberts, 2001) and flexure (Gao, 2013). A suite of schemes are available for such geometry estimation (e.g., Di and Gao, 2014b, 2017b; Gao and Di, 2015; Yu and Li, 2017a, 2017b; Qi and Marfurt, 2017), and various case studies have documented their efficiency in identifying planar seismic features like fractures. However, such geometric analysis often fails for stratigraphic features, such as channels, reefs, lobes, and overbanks. Instead, accurate stratigraphic interpretation becomes possible by performing seismic facies analysis, particularly the GLCM analysis that estimates the local arrangement of seismic amplitudes in 3D space (Gao, 1999; Eichkitz et al., 2013; Di and Gao, 2017c). Such GLCM tool is based on the fact that rock particles are packed in different ways with the depositional environment varying, and correspondingly, the reflection patterns are locally different in terms of their amplitude, frequency, and/or phase.

While depicting the target seismic feature from the surrounding ones, however, these techniques fail to extract the highlighted features as separate objects that can be readily fed into framework construction and modeling. For example, a salt body can be visually depicted as high
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Homogeneity and low contrast in GLCM maps (Gao, 2003), but isolating it from the surrounding patterns requires additional tools used in computer graphic and imaging processing. For example, normalized cuts (Lomask et al., 2007) detects salt domes by solving a global optimization problem. The active-contour-models method (Shafiq et al., 2015) starts with the initial boundary from interpreters and then gradually deforms it to fit the salt boundary observed in the attribute image. Wu (2016) incorporates discrete pickings by an interpreter into the detection process to guide accurate delineation of salt boundaries, especially in complicated zones with gaps or outliers. Ramirez et al. (2016) adopt the theory of sparse representation and apply it to automatically segment salt structures from 3D seismic dataset. Similarly, (semi-)automatic fault extraction has been popular in the past years with numbers of algorithms presented in this field, including ant tracking (Pedersen et al., 2002), Hough transform (AlBinhassan and Marfurt, 2003), eigenvector analysis (Barnes, 2006), dynamic time wrapping (Hale, 2013), motion vector (Wang et al., 2014), and more.

However, such object extraction often works for one certain structure at a time. Therefore, for a seismic dataset of multiple important features, such as faults and salt-bodies, both algorithms have to be performed individually, which doubles the required interpretation time and efforts. With the success of machine learning in audio/image/video understanding, various labeling and classification techniques have been introduced into the field of seismic interpretation, including facies analysis (Zhao et al., 2015), salt-body delineation (Alaudah et al., 2017; Di and AlRegib, 2017; Di et al., 2018a), and fault detection (Zheng et al., 2014; Huang et al., 2017; Di et al., 2017, 2018b; Alaudah and AlRegib, 2017). A comprehensive overview of machine learning in seismic interpretation can be found in AlRegib et al. (2018). Although the previous studies focus on certain seismic features, such classification algorithm can be easily extended for full-feature interpretation, given a training dataset of all important features well interpreted and labelled.

As observed in our testing, it is very efficient for training an optimal classifier from 3D seismic data; however, applying it for a seismic volume is a time-consuming process, particularly for large datasets, since the classification have to be repeated at every sample in the volume. To speed such process, this study presents a deconvolution neural network (DCNN) that is capable of understanding and labelling all features in an entire seismic section simultaneously, so that real-time seismic image interpretation can be achieved. Its added-values are verified through the success of labelling nine important features in the F3 block in the Netherlands North Sea.

Methodology

Figure 1 illustrates the proposed workflow for the DCNN-assisted real-time seismic image interpretation, which consists of four steps:

A. Training section labelling. Preparing a good training dataset is the key to the success of all supervised learning. In this study, 12 of the 583 inline sections in

Figure 1: The proposed workflow for real-time seismic image interpretation via the deconvolutional neural network (DCNN).

Figure 2: The original amplitude (a) and the manually labelled 9 classes of inline #350. It as well as 11 more sections are used for training the DCNN network.
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The F3 seismic dataset are manually labelled as 9 classes: (a) salt, (b) steep dips, (c) low coherency, (d) low amplitude, (e) low amplitude & dips, (f) high amplitude, (g) high amplitude & continuous, (h) grizzly, and (i) else. Figure 2 demonstrates the original amplitude and the corresponding manual labelling in the vertical section of inline #350.

B. DCNN training. The 12 labelled inline sections are then fed into training a DCNN model. Figure 3 illustrates the architecture of the simple DCNN used in this study. It contains 3 convolutional layers of 4, 8, 16 filters, respectively. The traditional 2x2 pooling is applied for reducing the dimensions of feature matrix, which resizes the image size from 256x256 to 32x32. Correspondingly, 3 deconvolutional layers are followed for recovering the reduced size 32x32 back to the original size 256x256, to ensure that the features are labelled at the correct locations in the seismic sections.

C. Accuracy verification. After training the DCNN model, we randomly extract a few sections from the F3 dataset and label them using the built DCNN model. Since the DCNN works directly on a seismic section, such process is at real time, so that it allows us to quickly verify the accuracy of the trained DCNN model. If not satisfied, these sections would be re-labelled and fed into updating the DCNN model. Figure 4 plots the learning curve of 1500 epochs. Particularly, the DCNN starts from random noises, and then become capable of depicting the outline of the 9 classes at about epoch #900. The following training is less obvious but gradually improves its accuracy that fine-tunes the labelling locally and reaches an accuracy of 0.8 when the training stops after 1500 epochs.

D. Volumetric processing. With the trained DCNN model well verified, it is applied to all 583 inline sections in the entire F3 survey, which provides us with a labelled volume of the same size as the F3 seismic volume.

Result analysis

After processing the F3 seismic dataset by the proposed workflow (Figure 1), Figure 5 displays a 3D view of the generated feature volume as well as its clipping to 6 randomly-selected sections. In general, the seismic volume is labelled correctly, particularly the salt domes and the overlaying strong continuous reflection in the bottom, and the steep dips in the middle that are of important depositional implications for sequential interpretation.

Next, for analyzing the accuracy of the DCNN labelling, we clip the feature volume (Figure 5) to 3 of the 12 inline sections...
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sections that were used in training, including #200, #400, and #600. As displayed in Figure 6, compared to the manual labelling, the patterns are correctly identified, such as the salt domes (in black), the overlaying strong continuous reflections (in cyan), and the steep dips (in orange). Finally, for the concern of over training, we clip the feature volume (Figure 5) to 3 sections, including inline #280, crossline #750, and time slice at 1700 ms, none of which was seen by the trained DCNN model (Figure 7). Similarly, they are labelled correctly in general, particularly these important structures like the salt domes (in black), the overlaying strong continuous reflection (in cyan), and the steep dips (in orange).

Conclusions

We have implemented the deconvolutional neural network (DCNN) into assisting seismic interpretation. The major superiority of such tool lies that the DCNN directly works on a seismic section and thereby is capable of label all the features in it at real time, which is more efficient than the traditional interpretation tools and the classification techniques (e.g., convolutional neural network). The success of the proposed DCNN on labelling the F3 block into 9 classes indicates its great potentials for assisting 3D seismic interpretation in a both fast and accurate manner.

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