Deep Convolutional Neural Networks for Seismic Salt-Body Delineation*

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Abstract

Salt-bodies are important subsurface structures with significant implications for hydrocarbon accumulation and sealing in offshore petroleum reservoirs, and accurate salt-body imaging and delineation is now greatly facilitated with the availability of 3D seismic surveying. However, considering the growing of seismic data size, the efficiency of interpreting a salt-body increasingly relies on the development of powerful computational interpretation tools that are capable of mimicking an experienced interpreter's intelligence. In recent years, with the success of machine learning in various disciplines, geoscientists desire to explore the massive seismic data in more intelligent ways and extract more information for better understanding the subsurface reservoirs. This study implements the emerging convolutional neural network (CNN) for the specific application of salt-body delineation from 3D seismic data, which is superior in two ways compared to the traditional sample-based multi-attribute classification schemes. First, the CNN takes into account the local seismic patterns for defining and learning the target salt-body features, so that the coherent noises and processing artifacts of distinct patterns can be effectively identified and excluded. Second, the CNN builds an optimal mapping relationship between the seismic signals and the salt-bodies directly from the reflection amplitude, which avoids the process of manual attribute selection where interpretation labor is intensive and interpreter bias might be introduced. The benefits of such CNN-based classification are demonstrated through applications to the synthetic SEG-SEAM dataset, which is featured with a complex intrusive in a folded Tertiary basin and challenges the existing salt-body interpretation tools. The preliminary results not only show good match between the detection and the original seismic images particularly in the zones where the reflection is weak and not discernable to the existing seismic attributes, but also indicate the great potential for applying the CNN tool to computer aided extraction of other important seismic objects (e.g., faults).

Introduction

Salt domes are of important geologic implications for robust characterization and modeling of hydrocarbon reservoirs in deep water, and the presence of a salt body can easily be recognized from three-dimensional (3D) seismic data due to the apparently weak and chaotic reflection patterns inside the salt. However, computer-aided salt body detection and interpretation is still a challenging topic, especially in the exploration areas of multiple salt bodies developed at different stages. In the past decades, great efforts have been devoted into this field by developing both new attributes and methods/algorithms to help delineate salt bodies from the surrounding non-salt features.

From the perspective of seismic attribute analysis, both edge detection and geometric and texture analysis are applicable for highlighting the boundaries of a salt dome, considering the significant variation of seismic signals across the boundaries. Particularly, the edge detection and geometric attributes evaluate the lateral changes in seismic amplitude, waveform, and/or reflector geometry, and correspondingly are capable of identifying the salt boundaries where the seismic pattern dramatically varies. Such attributes include the coherence (Bahorich and Farmer, 1995), the semblance (Marfurt et al., 1998), the similarity (Tingdahl ad de Rooij, 2005), various edge detectors used in the field of image processing (e.g., Luo et al., 1996; Zhou et al., 2007; Aqrawi et al., 2011; Di and Gao, 2014a; Asjad and Mohamed, 2015), the curvature (Roberts, 2001; Al-Dossary and Marfurt, 2006), the flexure (Gao, 2013; Di and Gao, 2014b, 2016, 2017a; Yu and Li, 2017; Qi and Marfurt, 2017). Similarly, as the first seismic texture attribute, the gray-level co-occurrence matrix (GLCM) was introduced from the field of image processing and is now widely used for seismic facies analysis (Gao, 2003, 2011; Eichkitz et al., 2013; Di and Gao, 2017b). Recently, with the increasing interest in deep-water reservoirs of salt bodies, more salt attributes have been developed, including the gradient of textures (GoT) (Hegazy and AlRegib, 2014), the seismic saliency (Drissi et al., 2008; Shafiq et al., 2016), and the salt likelihood (Wu, 2016).

By treating an attribute map as a digital image, further processing of such image aims at suppressing any false salt boundaries, which can then be considered as an image segmentation problem. Several methods have been proposed in the literature. For example, normalized cuts (e.g., Shi and Malik, 2000; Lomask et al., 2007) detects salt domes by solving a global optimization problem and thereby is less sensitive to local discontinuities; however, such method is computationally expensive and not suitable for processing large seismic datasets. The active-contour-models method (e.g., Zhang and Halpert, 2012; Haukas et al., 2013; Shafiq et al., 2015a) starts with the initial boundary from interpreters and then gradually deform it to fit the salt boundary observed in the attribute image. Similarly, 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. To avoid interpreter bias, Ramirez et al. (2016) adopt the theory of sparse representation and apply it to automatically segment salt structures from 3D seismic dataset with a minimum intervention from an interpreter.

However, considering the geologic complexities, in most cases, the use of a single salt attribute is insufficient for accurate delineation of the boundaries of a salt-body. For addressing such limitation, Meanwhile, considering the insufficiency of a single attribute to reliable salt detection, researchers (Berthelot et al., 2013; Halpert et al., 2014; Asjad and Mohamed, 2015; Guillen et al., 2015; Qi et al., 2016) have suggested integrating multiple attributes through machine learning-based techniques for improved detection accuracy and efficiency. The majority of the existing machine learning-based classification focuses on facies analysis, and a comparison of several unsupervised clustering/classification techniques in application of multiple attribute analysis could be found in Barnes and Laughlin (2002) and Zhao et al. (2015). Recently, such multi-attribute based classification has been implemented for the purpose of seismic structure interpretation, including faults and salt-bodies (e.g., Zheng et al., 2014; Di and AlRegib, 2017; Huang et al., 2017; Di et al., 2017a, 2017b; Guitton et al., 2017). However, these attribute-based techniques are greatly dependent on an experienced interpreter in selecting and preparing seismic attributes. Such process is labor intensive, and more importantly, has to be repeated when shifting the exploration from one dataset to another, considering the distinct geology in different areas.

In this paper, we propose a new method for accurately delineating the boundary of salt bodies by the emerging convolutional neural network (CNN), which is superior in two aspects over the traditional multi-attribute based techniques. First, the CNN network defines, learns, and classifies the salt-bodies based on local seismic reflection patterns, so that the seismic noises and processing artifacts of distinct patterns can be effectively identified and excluded. Second, the CNN network builds the mapping relationship between the seismic signals and the salt-bodies using the original seismic amplitude, instead of manually selected seismic attributes, so that the entire process requires less from an interpreters and the interpreter bias can be maximally avoided. The paper is organized as follows: First, we illustrate the workflow of the proposed method in details. Next, we demonstrate the results and compare them to those by the traditional techniques. Finally, based on the results of the experiments, we draw conclusions at the end of the paper.

Methodology

The proposed workflow is shown in Figure 1, which consists of three components as below. As the testing dataset, we use a subset (417 inlines x 417 crosslines x 168 samples per trace) of the 3D SEG-SEAM data that contains a complex salt intrusive and challenges the existing techniques of subsalt imaging in Tertiary basins, with emphasis on deepwater Gulf of Mexico (Orristaglio, 2016).

A. Training image preparation

For the supervised CNN classification in this study, we prepare the training images in three steps. First, the boundary of the salt-body in three vertical sections, including inline #4403, #4499, and #4595, are manually interpreted. Then, the 3 labelled inline sections are discretized to provide us with a total of 10,037 seeds on the target salt-body boundaries. Next, one image patch of the original post-stack amplitude is retrieved in a size of 31 crosslines by 31 samples centered about each of the labelled seeds. Finally, these images are resampled to be 32 by 32 to facilitate the convolution and pooling operations used in the CNN convolutional layers.

B. CNN Classifier training

Figure 2 illustrates the architecture of the CNN network used for salt-body classification in this study. In particularly, it consists of two convolutional layers followed by one fully connected layer. The input seismic images are 32 by 32. The convolution masks have a size of 9 by 9. The convolutional layer generates eight features. The 2x2 maximum pooling is used to reduce the dimensions of output features after convolution and hence to control overfitting. The dropout technique (Hinton et al., 2012) is also used to avoid overfitting by preventing complex co-adaptations on training data. The fully connected layer has 2048 neurons, and the softmax cross entropy is computed for measuring the probability error between the classification and the true labels. The prepared 420,336 images from the three sections are used for training the CNN network in 300 epochs. Cross validation is applied for verifying the accuracy of the trained CNN classifier. The activation function at all neurons is initialized as random noises in normal distribution with the standard deviation of 0.1, and are updated while the training continues.

C. Volumetric processing

Finally, the trained CNN classifier is applied to the entire seismic survey for generating a salt-body volume. At each seismic sample, an image patch of 31 crosslines by 31 samples is first retrieved from the original amplitude and then resampled into 32 by 32. Then its label is predicted by the trained CNN classifier and assigned to the central sample. Correspondingly, the generated salt-body volume is of the same size as the original seismic data (417 inlines x 417 crosslines x 168 samples per trace).

Results Analysis

For demonstrating the accuracy of the proposed CNN approach, we first compare the results with the traditional multi-attribute based classification methods. Figure 3 displays the comparisons in the three inline sections with manual interpretation, among which we notice that the CNN result is clean and closest to the manual interpretation. On one hand, compared to the SVM, the neural networks (MLP and CNN) significantly reduces the false-positive ratio, so that these samples nearby the salt dome are not misclassified as thick salt boundaries. On the other, the SVM and MLP fails in the zones of weak reflections where the seismic attributes cannot identify the salt boundaries (denoted by circles), whereas the CNN successfully identifies these features and builds a robust mapping relationship between them and the seismic signals.

Next, for addressing the concern of over training, Figure 4 displays the 3D view of the salt-body surface and the clipping to six randomly selected vertical sections that were not used in the training process. It is clear that, the CNN classification successfully detects the salt-body boundaries as thin curves, indicating that the trained CNN classifier is capable of learning the target seismic features from the original post-stack seismic amplitude and detecting the identical ones accurately.

Conclusions

Reliable detection of subsurface salt bodies from 3D seismic data is essential for reservoir characterization and modeling. This study has presented a new method for salt boundary delineation based on the emerging convolutional neural network (CNN) technique, which is superior in two aspects over the traditional multi-attribute based techniques. First, the CNN network defines, learns, and classifies the salt-bodies based on local seismic reflection patterns, so that the seismic noises and processing artifacts of distinct patterns can be effectively identified and excluded. Second, the CNN network builds the mapping relationship between the seismic signals and the salt-bodies using the original seismic amplitude, instead of manually selected seismic attributes, so that the entire process requires less from an interpreters and the interpreter bias can be maximally avoided. The good match between the generated salt-probability volume and the original seismic images not only verifies the capability of the CNN tool on learning seismic features, but also indicates greater potential of the state-of-the-art machine learning techniques for more advanced seismic data analysis, such as real-time feature segmentation.

Acknowledgments

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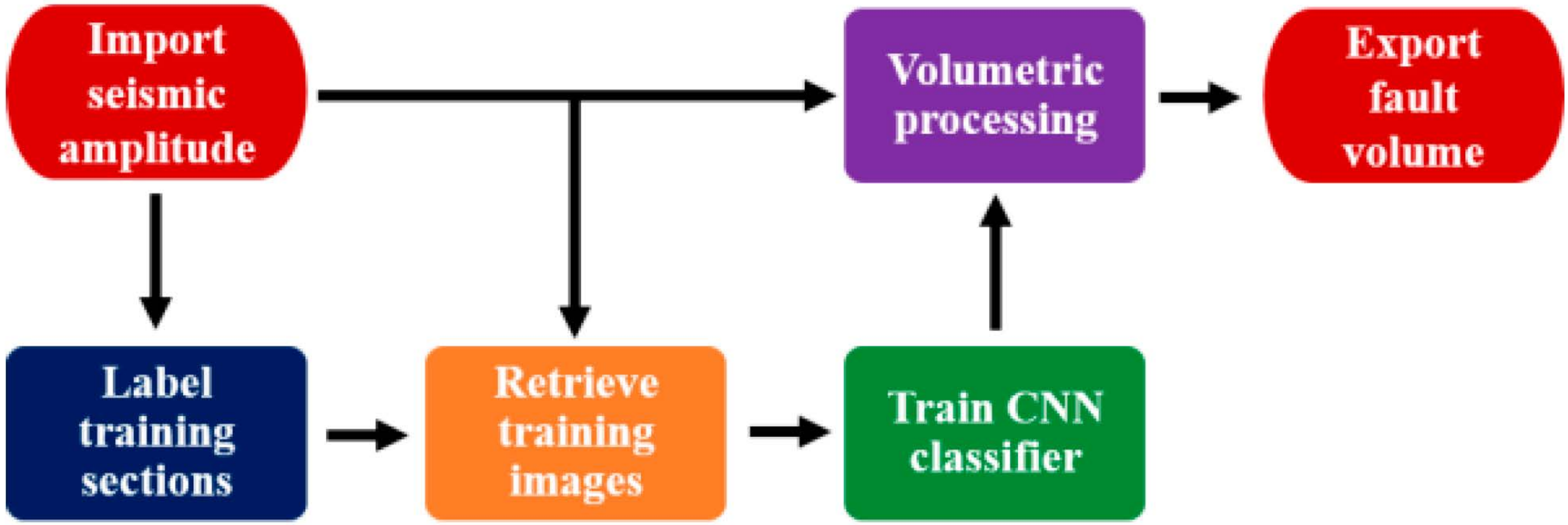

Figure 1. The diagram for illustrating the proposed workflow of CNN-based seismic salt-body delineation with three major components: training image preparation, CNN classifier training, and volumetric processing.

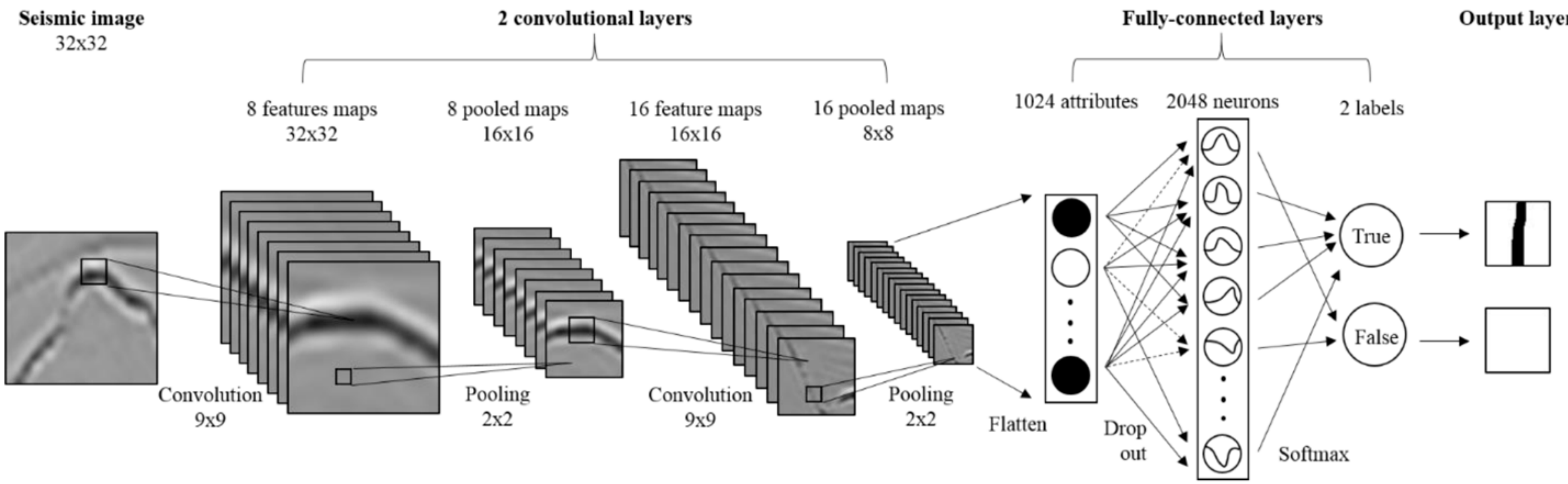

Figure 2. The diagram for illustrating the architecture of the convolutional neural network (CNN) network used in this study for salt-body delineation.

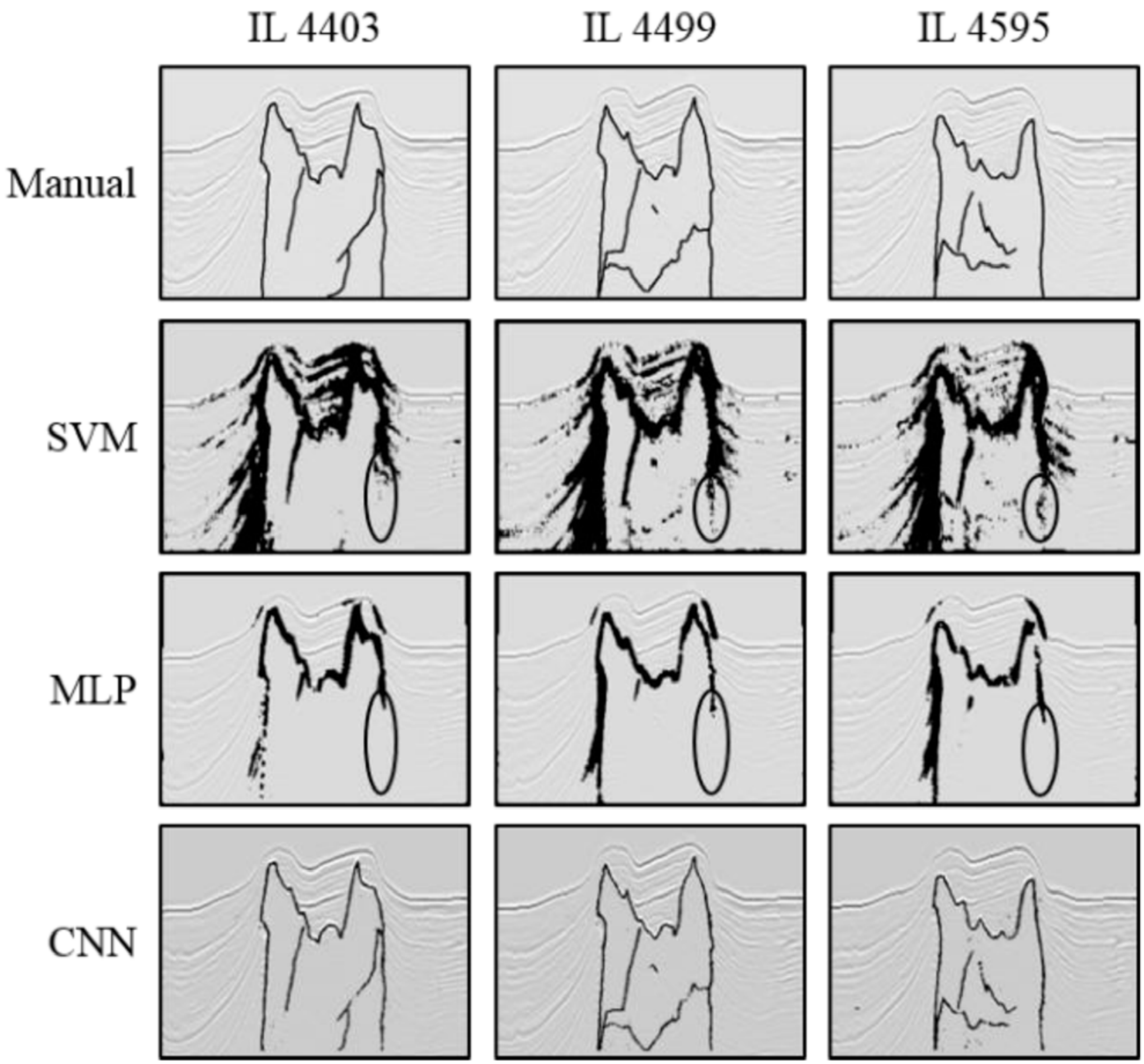

Figure 3. A comparison of labeling the salt-body boundaries using the traditional multi-attribute based support vector machine (SVM) and multi-layer perception (MLP) and the proposed amplitude-based convolutional neural network (CNN) in the inline sections #4403, #4499, and #4595.

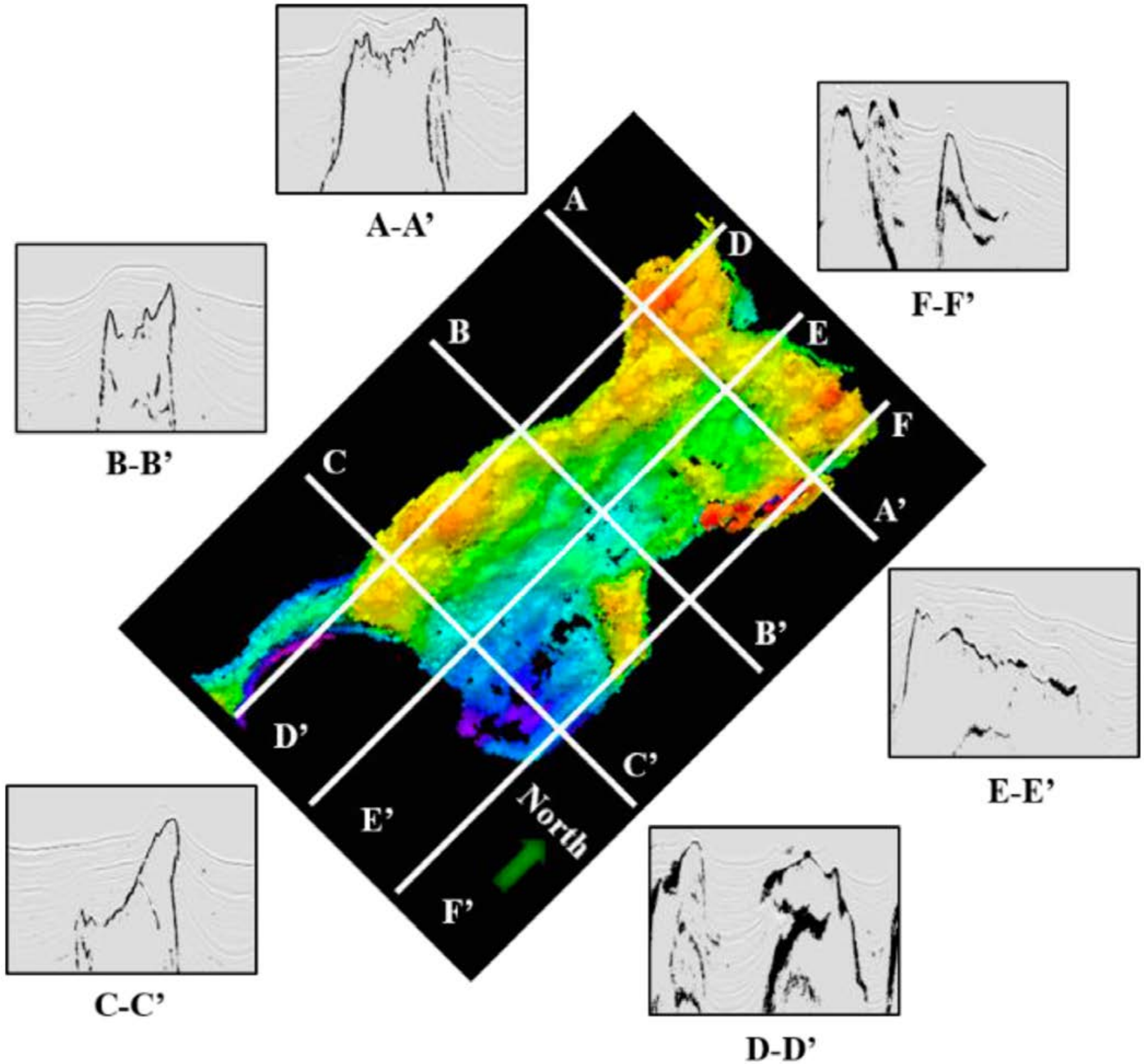

Figure 4. The 3D view of the detected salt-body boundaries, which is also clipped to six vertical sections for analyzing its accuracy. Note that none of these sections is fed into training the CNN classifier.