A comparison of seismic saltbody interpretation via neural networks at sample and pattern levels

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ABSTRACT

Saltbodies are important subsurface structures that have significant implications for hydrocarbon accumulation and sealing in petroleum reservoirs, and accurate salt-body imaging and delineation is now greatly facilitated with the availability of three-dimensional seismic surveying. However, with the growing demand for larger survey coverage and higher imaging resolution, the size of seismic data is increasing dramatically. Correspondingly, manual saltbody interpretation fails to offer an efficient solution, particularly in exploration areas of complicated salt intrusion history. Recently, artificial intelligence is attracting great attention from geoscientists who desire to utilize the popular machine learning technologies for evolving the interpretational tools capable of mimicking an experienced interpreter’s intelligence. This study first implements two popular machine learning tools, the multi-layer perceptron and the convolutional neural network, for delineating seismic saltbodies at sample and pattern levels, respectively, then compares their performance through applications to the synthetic SEAM seismic volume, and moreover tentatively investigates what contributes to the better convolutional neural network delineation. Specifically, the multi-layer perceptron scheme is capable of efficiently utilizing an interpreter’s knowledge by selecting, pre-conditioning and integrating a set of seismic attributes that best highlight the target saltbodies, whereas the convolutional neural network scheme makes it possible for saltbody delineation directly from seismic amplitude and thus significantly reduces the dependency on attribute selection from interpreters. It is concluded that the better performance from the convolutional neural network scheme results from two factors. First, the convolutional neural network builds the mapping relationship between the seismic signals and the saltbodies using the original seismic amplitude instead of manually selected seismic attributes, so that the negative impact of using less representative attributes is virtually eliminated. Second and more importantly, the convolutional neural network defines, learns and identifies the saltbodies by utilizing local seismic reflection patterns, so that the seismic noises and processing artefacts of distinct patterns are effectively identified and excluded.

Key words: Interpretation, Seismics, Computing aspects.

1 INTRODUCTION

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

From the perspective of seismic attribute analysis, edge detection, geometric estimation and texture analysis are all applicable for highlighting a saltbody, considering the significant variation of seismic signals across the saltbody boundaries. Particularly, the edge detection and geometric attributes evaluate the lateral changes in seismic amplitude, waveform and/or reflector geometry, and correspondingly the salt boundary is detected where the seismic pattern dramatically varies. Such attributes include the coherence (Bahorich and Farmer 1995), semblance (Marfurt et al. 1998), similarity (Tingdahl and de Rooij 2005), various edge detectors used in the field of image processing (e.g. Luo, Higgs and Kowalik 1996; Zhou et al. 2007; Aqrawi, Boe and Barros 2011; Di and Gao 2014; Amin and Deriche 2015), curvature (e.g. Roberts 2001; Al-Dossary and Deriche 2006) and flexure (Gao 2013; Di and Gao 2017a). Similarly, as the first seismic texture attribute, the grey-level co-occurrence matrix (GLCM) was introduced from the field of image processing and is now widely used for seismic facies analysis (e.g. Gao 2003; Eichkitz, Amtmann and Schreilechner 2013; Di and Gao 2017b). Recently, with the increasing interest in deep-water reservoirs of saltbodies, more salt attributes have been developed, for example the gradient of textures (GoT) (Hegazy and AlRegib 2014), the salt likelihood (Wu 2016) and the seismic saliency (Shafiq et al. 2016). Specifically, the GoT attribute evaluates the perceptual dissimilarity of the seismic texture between two adjacent analysis windows and thereby is capable of delineating the saltbody boundaries, where apparent variations of seismic texture are often observed (Hegazy and AlRegib 2014; Shafiq et al. 2015; Wang et al. 2015). The salt likelihood attribute is derived from seismic structure tensors (van Vliet and Verbeek 1995; Weickert 1997; Fehmers and Hocker 2003) and highlights the saltbody boundaries by measuring the linearity or planarity of seismic reflection (Wu 2016). The idea of seismic saliency originates from the modelling of the human vision system and is capable of highlighting the zones in a seismic volume, which receive highest attention from the interpreters (Drissi, Chonavel and Boucher 2008; Shafiq et al. 2016). However, while implemented for saltbody detection, in most cases, a single seismic attribute often quantifies the variation of seismic signal by a certain statistic operator (e.g. correlation) and thus is insufficient for comprehensively representing the seismic features often of complexities, including the saltbody delineation discussed in this paper.

Such insufficiency can be addressed with the aid of computer vision and machine learning, and geophysicists have been devoting their efforts into utilizing them for seismic data analysis (e.g. McCormack 1991). For example, integrating multiple attributes through machine learning techniques has proven efficient for improving interpretation accuracy (Berthelot, Solberg and Gelius 2013; Halpert, Clapp and Biondi 2014; Zheng, Kavousi and Di 2014; Amin and Deriche 2015; Guillen et al. 2015; Qi et al. 2015; Di and AlRegib 2017; Di, Shafiq and AlRegib 2018). Meanwhile, recently the convolutional neural network is exclusively investigated and implemented for seismic interpretation, particularly fault detection (e.g. Di, Shafiq and AlRegib 2017; Huang, Dong and Clew 2017; Guitton, Wang and Guitton 2017) and saltbody delineation (e.g. Di, Wang and AlRegib 2018a; Waldeiland et al. 2018; Zeng, Jiang and Chen 2018; Shi, Wu and Fomel 2019). However, little work has been done towards an in-depth comparison of these techniques in seismic saltbody delineation.

In this paper, we propose implementing and comparing two popular machine learning algorithms, including the multi-layer perceptron (MLP) and the convolutional neural network (CNN), which delineates the seismic saltbodies at sample and pattern levels, respectively. The paper is organized as follows. First, we illustrate the workflows of the proposed MLP- and CNN-based seismic saltbody delineation in details. Next, their performance is compared on the synthetic SEAM seismic dataset. The following is an investigation of two factors that contribute to the better CNN delineation. Finally, we discuss the potential work in the future and draw conclusions at the end of the paper.

2 METHODOLOGY

For the convenience of illustrating and testing the proposed workflows, we use a subset (417 inlines, 417 crosslines, 168 samples per trace) of the three-dimensional (3D) SEG-SEAM dataset, which covers a complex salt intrusive in Tertiary basins and challenges the existing techniques of subsalt imaging particularly in Deepwater Gulf of Mexico (Oristaglio 2016). Figure 1 displays the post-stack amplitude of the inline section #4403, in which the majority of the salt intrusive is clearly imaged as bodies of chaotic reflections. Additionally, we note that (a) the saltbody boundary on the right flank...
becomes less discernable as it goes below 4.0 seconds (denoted by the oval), and (b) inside the saltbody a few linear or curved reflection events are recognizable (denoted by the arrows), which implies the complexities of its rising from the bottom.

For supervised machine learning schemes including the multi-layer perceptron (MLP) and convolutional neural network (CNN) schemes used in this study, preparing a proper annotated datasets is essential for network training, evaluation and prediction. In the field of image processing and recognition, there exist a number of such annotated datasets of natural images such as the MNIST (LeCun et al. 1998) and ImageNet (Fellbaum 2005). However, open-source expert annotations are lacking in the domain of seismic data analysis and interpretation. In this study, we prepare the training and testing data by manually annotating the saltbody boundaries observed in five inline sections including inline #4403 (Fig. 2), #4499, #4595, #4451 and #4547. Specifically, the first three sections are used for training both the MLP and CNN models that provides a total of 210,168 training samples, whereas the last two sections are reserved for model testing and evaluation. It is necessary to mention the following.

(a) The amount of training data is only 0.7% of the available seismic survey. From such a small training set, as shown below, both MLP and CNN workflows are capable of delineating the salt boundaries throughout the entire SEAM dataset. Meanwhile, a number of mispredictions, particularly the false positives, are identified, which can be further avoided by annotating and providing more training sections.

(b) Considering the dominance of non-salt boundaries in the training sections (Fig. 2), the imbalance between the non-salt samples and the salt samples used for the MLP and CNN training is addressed by randomly retrieving the same amount of non-salt samples as that of the salt ones. Other data augmentation techniques, such as image flipping and rotation that is often used in CNN-based image processing, are highly recommended for increasing the amount of salt samples in the future.

(c) In our annotations, besides the top of salt we also tentatively label the inner lineaments (denoted by arrows in Fig. 1) as boundaries between saltbodies formed at different stages. More work is expected for verifying and improving the annotations by experienced seismic interpreters, particularly when the research focus switches from algorithm development in this paper to real case studies in the future.

2.1 Sample-level multi-layer perceptron

The multi-layer perceptron (MLP) is a class of feedforward artificial neural network consisting of one input layer, at least one hidden layer and one output layer, each of which is fully connected with its neighbouring layers. Figure 3 illustrates the architecture of a typical MLP network used for seismic pattern classification, such as gas chimney (Meldahl et al. 1999), fault detection (Tingdahl and de Rooij 2005; Zheng et al. 2014)
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Figure 3 The diagram for illustrating the architecture of the MLP model used in this study for seismic saltbody delineation at sample level. Specifically, $m = 9$, $q = 3$ and $p = 32$.

Figure 4 The workflow of the proposed MLP-based seismic saltbody delineation at sample level, which consists of four components: (a) seismic attribute selection, (b) training sample annotation, (c) MLP model training and (d) volumetric prediction.

Figure 5 The post-stack amplitude of the crossline section #4499 used for illustrating the nine selected seismic attributes (Fig. 6) and the automatically extracted CNN attributes (Figs 14 and 15).

and saltbody delineation in this study. Specifically, the input layer contains $n$ neurons, each of which corresponds to one of the labelled training samples and is represented as an array of the selected $m$ seismic attributes at each sample. The output layer has two neurons – true and false – which here represent saltbody boundary and non-boundary, respectively. These two layers are connected by $q$ hidden layers, each of which contains $p$ neurons. In math, each neuron in the hidden layer(s) and the output layer is represented by a pair of weight $w$ and bias $b$, which is optimized through training to construct the best mapping relationship between the two outputs and the $m$ selected seismic attributes. In addition is the use of activation function (Hahnloser et al. 2000) for introducing the non-linearity and the dropout (Hinton et al. 2012) for addressing the overfitting issue. In this study, the MLP network has $q = 3$ hidden layers of $p = 32$ neurons in each layer and correspondingly consists with about 2500 trainable parameters. The rectifier linear unit (ReLU) (Nair and Hinton 2010) is used as the activation function for all neurons, and the dropout of 0.5 is applied on the three hidden layers.

Figure 4 illustrates the proposed MLP-based workflow for seismic saltbody delineation at sample level, which consists of four components: (a) seismic attribute selection, (b) training data annotation, (c) MLP model training and (d) volumetric prediction. Specifically, nine seismic attributes are selected from the available attribute library (Chopra and Marfurt 2005) and pre-computed from the original seismic amplitude, including seven grey-level co-occurrence matrix (GLCM) attributes (contrast, dissimilarity, energy, entropy, homogeneity, standard deviation and variance) and two discontinuity attributes (semblance and similarity). All of them are normalized.
2.2 Pattern-level convolutional neural network

The convolutional neural network (CNN) is also a class of feedforward artificial neural networks, in which the connectivity pattern between neurons is inspired by the organization of the animal visual cortex (Matsugu et al. 2003). A CNN often consists of an input layer, an output layer and multiple hidden layers that are convolutional, pooling and/or fully connected. Figure 8 illustrates the architecture of the simple CNN used for seismic saltbody delineation in this study, which consists of two convolutional layers and one fully connected layer. The formers generate 8 and 16 features, respectively, by performing a set of $9 \times 9$ convolution masks. The fully connected layer has 2048 neurons. Correspondingly, there are a total of about 5.8 million trainable parameters. In addition, for controlling the problem of overfitting, the $2 \times 2$ maximum pooling is used to reduce the dimensions of output features. Among various types of activation functions, the ReLU (Nair and Hinton 2010) is used in both convolutional and fully connected layers; and for preventing complex co-adaptations on training data, the dropout of 0.8 is applied to the fully connected layer.

Figure 9 illustrates the proposed CNN-based workflow for seismic saltbody delineation at pattern level, which consists of three components: (a) training data annotation, (b) CNN model training and (c) volumetric prediction. Compared to the sample-level MLP classification (Fig. 4), the CNN workflow avoids the first component of seismic attribute selection, and thus requires relatively less prior knowledge and effort.
Figure 7 The normalized contribution of the nine seismic attributes on predicting the target saltbody boundaries, in which the GLCM contrast contributes most (>20%), whereas the similarity gives least contribution (<1%).

Figure 8 The diagram for illustrating the architecture of the CNN model used in this study for seismic saltbody delineation at pattern level. Specifically, it consists of two convolutional layers and one fully connected layer.

Figure 9 The workflow of the proposed CNN-based seismic saltbody delineation at pattern level, which consists of three components: (a) training image annotation, (b) CNN model training and (c) volumetric processing.

3 RESULT ANALYSIS

After training the multi-layer perceptron (MLP) and convolutional neural network (CNN) models, we then compare their performance from the perspective of both training and prediction. First, the 50-epoch training process is shown in Fig. 11, which represents the cross-entropy loss between the machine predictions and the manual annotations. By comparing the training loss, the CNN outperforms the MLP in two aspects. First, the convergence occurs much sooner in terms of the epoch number when the loss significantly reduces, indicating the better capability of the CNN in fast learning. Second, the loss is successfully minimized close to 0, whereas the MLP can only reduce the loss to about 0.2, indicating the incapability of the MLP in fully understanding the seismic signals and accomplishing the task of salt delineation. Such incapability is confirmed by the presence of massive false positives in the MLP prediction as shown in Fig. 12 and Table 1 and results from the insufficiency of the selected nine seismic attributes in representing the target saltbody boundaries.

from interpreters in seismic data pre-processing, attribute selection, extraction and conditioning. For training the pattern-level CNN model, we first discretize the three labelled inline sections as a set of $31 \times 31$ image patches centred about each of the 210,168 annotated samples. Figure 10 displays 25 image patches that are randomly selected from the training dataset. For fair comparison with the MLP workflow, no additional data augmentation, such as image rotation and flipping, is applied in this work.
Next, we apply both models to the two testing inline sections (#4451 and #4547), and Fig. 12 displays the delineation as well as the manual annotations. It is clear that both MLP and CNN successfully delineate the target saltbody boundaries. However, the MLP produces a large number of false positives, which thickens the delineated boundaries (denoted by the ovals); such observation is also supported in the corresponding confusion matrices (Tables 1 and 2), from which the CNN scheme leads to lower false positive rate. Meanwhile, both overall accuracy and F1 score improve from the MLP scheme to the CNN scheme, which also indicates the better performance by the pattern-level CNN. Therefore, it is concluded that the CNN-based scheme is capable of providing relatively better saltbody delineation for the given SEAM seismic dataset.

Finally, the trained CNN model is applied to the SEAM dataset and Fig. 13 displays the generated top of salt in the map view, which is similar to the initial model designed by the experts.
Table 1  The confusion matrix of applying the proposed MLP scheme to the two testing sections

<table>
<thead>
<tr>
<th></th>
<th>Salt</th>
<th>Non-salt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Salt</td>
<td>3964</td>
<td>744</td>
</tr>
<tr>
<td>Non-salt</td>
<td>11,013</td>
<td>124,391</td>
</tr>
</tbody>
</table>

Overall Accuracy: 0.92
False-positive rate: 0.08
F1 score: 0.40

Table 2  The confusion matrix of applying the proposed CNN scheme to the two testing sections

<table>
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<tr>
<th></th>
<th>Salt</th>
<th>Non-salt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Salt</td>
<td>2532</td>
<td>1835</td>
</tr>
<tr>
<td>Non-salt</td>
<td>960</td>
<td>101,485</td>
</tr>
</tbody>
</table>

Overall accuracy: 0.97
False-positive rate: 0.01
F1 score: 0.64

Note the improved overall accuracy and F1 score as well as reduce false positive rate compared to the MLP scheme (Table 1).

for generating the synthetic SEAM dataset. In addition, for analysing its accuracy, the delineation is clipped to six vertical sections, including three inlines and three crosslines, none of which the CNN has seen during its training. Similar to Fig. 12, in spite of a small number of false positives, the CNN delineation (shown as the black curves) provides good match with the original seismic images. Such misprediction could be further eliminated by fine tuning of the CNN model with more expert-annotated sections.

4 WHAT MAKES CONVOLUTIONAL NEURAL NETWORK BETTER

As demonstrated in Section 3, the pattern-level convolutional neural network (CNN) scheme (Fig. 9) performs better than the sample-level multi-layer perceptron (MLP) scheme (Fig. 4), and this section aims at a tentative investigation of the factors that contribute to the better CNN performance. If comparing the MLP model (Fig. 3) to the CNN model (Fig. 8), we note that both CNN and MLP architectures are similar in the back-end of using one or more fully connected layers to build the mapping relationship between the attributes (or features) and labels, whereas they differ from the perspective of how the attributes (or features) are generated and provided. Specifically, the seismic attributes used in the MLP workflow (Fig. 4) are often manually selected based on an interpreter’s knowledge and pre-computed from the given seismic cube, whereas the CNN generates a set of features by itself through its convolutional layers. Here for the convenience of description, we denote such features generated in the CNN also as attributes. Therefore, the better CNN performance most likely results from the automatic attribute generation through the convolutional layers, in which we identify two factors, with one being the automatic extraction of attributes (or features) and the other being the feeding of attribute maps into fully connected layers (Di, Wang and AlRegib 2018b). Each of the two factors is illustrated and investigated through an experiment below.

4.1 Factor A

The automatic attribute generation by the CNN convolutional layer(s). For fair comparison with the nine seismic attributes (Fig. 6), we first apply the trained CNN architecture (Fig. 8) to the entire SEAM cube, not for salt prediction in this task but to export the 8 and 16 CNN attributes from the two convolutional layers, respectively. Therefore, each of the 24 CNN attributes is of the same dimension as the original seismic amplitude and the 9 seismic attributes. The comparison is in twofold. First, we clip three sets of attributes, the seismic attributes (Fig. 6), the 8 first-layer CNN attributes (Fig. 14) and the 16 second-layer CNN attributes (Fig. 15) to the same vertical section of crossline #4499 and compare them from...
Figure 14 The 8 attributes automatically generated from the first CNN convolutional layer. The corresponding convolution masks are displayed in the bottom-left corner. Note the less physical meaning compared to the nine seismic attributes (Fig. 6).

Figure 15 The 16 attributes automatically generated from the last (second) CNN convolutional layer. The corresponding convolution masks are displayed in the bottom-left corner. Note the less physical meaning compared to the nine seismic attributes (Fig. 6).

the perspective of an interpreter’s vision system (Figs 6, 14 and 15). It is noted that the seismic attributes are visually more interpretable, from which the saltbody boundaries are explicitly differentiable in either low or high value from the surrounding non-salt patterns. On the contrary, the CNN attributes are of less physical meaning, which remains similar to the original seismic amplitude (Fig. 5). Therefore, the vision system of seismic interpreters is more sensitive to the seismic attributes than the CNN attributes.

Second and from the perspective of artificial intelligence, we build three MLP networks of the same architecture and compare their results, each of which corresponds to one of the three attribute sets, including the 9 seismic attributes (Fig. 6), the 8 first-layer CNN attributes (Fig. 14) and the 16 second-layer CNN attributes (Fig. 15). Figure 16 displays the delineated saltbody boundaries in the inline section #4499 from the three MLP networks. We note that the CNN attributes lead to similar saltbody delineation to that from the nine manually selected seismic attributes (Fig. 6), with subtly better delineation for the inner boundaries (denoted as circle in Fig. 16b,c). Therefore, it is fair to conclude that although the CNN attributes are of little physical meaning and difficult for the human vision system to parse and understand, they can be well analysed and utilized by artificial intelligence (e.g. MLP model) for identifying the target saltbodies in a similar way to the traditional seismic attributes.
Figure 16 The comparison of the delineating saltbody boundaries (in black) in the vertical section of inline #4499 from using the sample-level MLP classification from various attributes, including (a) the 9 manually selected seismic attributes (Fig. 6), (b) the 8 first-layer CNN attributes (Fig. 14) and (c) the 16 second-layer CNN attributes (Fig. 15). Compared to the seismic attributes, the CNN attributes leads to better delineation of the linear boundaries inside the saltbody (denoted by ovals). Such improvement verifies the contribution of the automatic attribute generation by the convolutional layer(s) in the CNN architecture (Fig. 8) to better saltbody delineation.

4.2 Factor B

The feeding of attribute maps to fully connected layers, which takes into account the local patterns for building the mapping relationship between the attributes and the target seismic features. For verifying it, we feed the three attribute sets, including the 9 seismic attributes (Fig. 6), the 8 first-layer CNN attributes (Fig. 14) and the 16 second-layer CNN attributes (Fig. 15), into a single MLP network in two ways, with one of the attribute values only at the samples and the other of the local attribute patterns centred at the samples, which are denoted as sample-level classification and pattern-level classification, respectively. Figure 17 compares the results of the inline section #4499, which provides us with two observations. First, the noise robustness is significantly improved with the pattern-level classification, since the seismic noises are often of distinct patterns from the linear or curved saltbody boundaries. Second, the use of the local pattern allows the MLP classifier to define and learn the salt-body boundaries in the zones of weak signals (denoted by rectangle), which are simply ignored by the sample-level classification. The benefits

Figure 17 The comparison of the saltbody boundary delineation (in black) in the vertical section of inline #4499 using the sample- and pattern-level MLP classification from the seismic and CNN attributes. Both reduced noise level and improved detection particular in the zones of weak reflection (denoted by rectangle) verify the contribution of incorporating the local attribute patterns in the CNN architecture (Fig. 8) for better saltbody delineation.
Figure 18 The comparison of the learning accuracy using the sample- and pattern-level MLP classification from the CNN attributes to verify the contribution of using attribute maps in the CNN architecture (Fig. 8) to better saltbody boundary delineation by incorporating the local attribute patterns, with the curve from the sample-level first-layer attributes in red, the curve from the sample-level second-layer attributes in yellow, the curve from the pattern-level first-layer attributes in black and the curve from the pattern-level second-layer attributes in blue.

Figure 18 demonstrates the accuracy curves of training the sample- and pattern-level MLP from the 24 CNN attributes. Specifically, the sample-level classification from the first-layer CNN attributes is limited to its accuracy of 75% (denoted by the red curve), whereas the accuracy is improved to 99% by the pattern-level classification from the second-layer CNN attributes (denoted by the blue curve). The improvement in the accuracy can be divided into two parts. First, the use of the second-layer CNN attributes helps improve the accuracy by ~10% (denoted by the yellow curve), which represent the contribution by generating and optimizing the CNN attributes from the first layer to the second layer. Second, the accuracy is further improved by ~15% when the pattern-level classification is performed, which represents the contribution of using attribute patterns to the better CNN performance (Fig. 8). Therefore, in this experiment the delineation is more improved by extending the classification from sample level to pattern level (Fig. 17) than from automatically generating the CNN attributes (Fig. 16), and correspondingly a tentative conclusion is that among the two factors the pattern-level classification (Factor B) contributes more than the automatic attribute generation (Factor A).

5 DISCUSSIONS

The popular convolutional neural network (CNN) technology has been tentatively implemented and investigated for saltbody delineation from three-dimensional (3D) seismic data, which demonstrates superior performance over the traditional sample-level machine learning schemes (e.g. multi-layer perceptron). The promising results indicate its vast applicability for solving problems in the domain of seismic data analysis and interpretation. For example, more efforts could be made towards efficient seismic saltbody delineation from the following four aspects.

First, the CNN architecture used in this study (Fig. 8) is designed for 2D images, which runs individually per seismic section and ignores the lateral continuity of seismic features through adjacent sections. However, the geometry of a saltbody is often continuous from one section to another. Such continuity can be incorporated by implementing 3D CNN that treats seismic features as actions in a video (e.g. Ji et al. 2013; Maturana and Scherer 2015). Figure 19 demonstrates the improved detection when 3D CNN is implemented to incorporate the lateral continuity of seismic features into the learning process. In turns, the 3D convolution requires more computational resources (e.g. GPU).

Second, the scope of this study focuses on investigating the capability of the CNN in learning seismic features, and the simple binary classification is used for recognizing only the saltbody boundaries in a seismic volume. However, salt structures are complex from the perspective of geology, including the canopies, pillows and diapirs (Fig. 20a) (e.g. Fossen 2016). Interpreting all these structures requires performing a multi-class CNN classification, so that a more comprehensive understanding of a saltbody can be obtained to facilitate the interpretation of its formation and impacts in geology. For achieving such goal, preparing the corresponding training datasets is of high priority, which needs a collaboration with experienced geologists and interpreters to label all these salt structures that have been clearly imaged in 3D seismic data (Fig. 20b).

Third, in the proposed workflow (Figs 4 and 9), extracting of the salt-boundary volume is conducted by repeating the CNN classification from one sample to another through...
Figure 19 A comparison of delineating the saltbody boundaries using the 2D and 3D CNN in three sections, including inline #6971, crossline #4499 and time #3492. Note the improved continuity of the detection when incorporating the lateral continuity of seismic features by 3D CNN.

the entire volume. However, such sample-wise prediction is time consuming and fails to meet the need of fast interpretation particularly for large seismic datasets. Such limitation could be addressed by expanding the CNN classification to be section- or even volume-wise. Plenty of similar work has been done in the field of image processing for object localization and segmentation and could be introduced for interpreting seismic volumes (Fig. 21). For the specific problem of saltbody delineation, one approach is to first locate the saltbody by the R-CNN algorithm (Ren et al. 2015) and then adjust the bounding box for matching the actual seismic images by the optimal path picking (Wu, Fomel and Hudec 2018). A more convenient solution is to implement the fully convolutional network (Long, Shelhamer and Darrell 2015) for real-time

Figure 20 The illustration of structure complexities of salt in the subsurface. Top: the geologic model of various salt structures, including the canopies, walls, anticlines, rollers, pillows, sheets, glaciers, stocks, sheets and welds (Fossen 2016). Bottom: a real example of seismic imaging of various salt structures within the Angola Block 22, including the tongues, canopies and detached diapirs (Duval, Mann and Houston 2015).

Figure 21 The analogy of real-time seismic structure interpretation through object localization and segmentation using the pattern-level CNN networks. The natural image is provided by Lin et al. (2014).
Figure 22 The saltbody delineation (in red) of the F3 block by the trained MLP (a) and CNN (b) models from the SEAM dataset. Note the limited detection due to the distinct patterns of the target structure from one area to another.

seismic pattern interpretation, including saltbody (Di, Gao and AlRegib 2019).

Fourth and more importantly, the proposed workflows (Figs 4 and 9) focuses on training the optimal multi-layer perceptron (MLP) and CNN models from the SEAM dataset and then applying them to the same dataset. The MLP/CNN applications to the domain of seismic interpretation can be further broadened if a trained model is applicable to multiple datasets. However, the seismic expression of saltbodies often varies from one exploration to another due to the geologic complexities, and correspondingly, the delineation accuracy is limited when the MLP/CNN model trained from the SEAM data is simply applied to another dataset, such as the F3 block (Fig. 22). More work is needed for solving such a limitation. The optimal solution is to prepare comprehensive training datasets that cover the variations of seismic saltbodies as detailed as possible and train a global saltbody model, which is readily applicable to any new seismic datasets. This is challenging and cannot be achieved in a short term. An alternative approach is to integrate transfer learning technology (Yang, Hanneke and Carbonell 2013) with a pre-trained model, so that it can be rapidly updated by providing a small amount of manual annotations when a new dataset is given.

6 CONCLUSIONS

Reliable delineation of subsurface saltbodies from three-dimensional (3D) seismic data is essential for reservoir characterization and modelling. This study has compared the performance of the popular multi-layer perceptron (MLP) and convolutional neural network (CNN) techniques on seismic saltbody delineation, and investigated the better CNN performance from two perspectives. First, the CNN builds the mapping relationship between the seismic signals and the saltbodies using the original seismic amplitude, instead of manually selected seismic attributes, so that the entire process requires less from an interpreter and the use of a less efficient seismic attribute can be maximally avoided. Second and moreover, the CNN defines, learns and classifies the saltbodies based on local seismic reflection patterns, so that the seismic noises and processing artefacts of distinct patterns can be effectively identified and excluded.

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