Introduction

Computer-aided subsurface object detection (e.g., faults and saltbodies) has been the recent focus of geophysical research on hydrocarbon exploration and production from 3D seismic surveying. Traditionally, skilled interpreters delineate such objects by visually examining seismic amplitude, waveform, geometric configuration, as well as various attributes on a suite of 2D vertical lines; correspondingly, the target object would be posted on a map that well depicts its shape and/or geometry. However, with the increasing demand of high-resolution seismic interpretation, the size of 3D seismic volumes is rapidly rising, and additionally, hundreds of new seismic attributes have been developed for assisting seismic feature analysis in the past few decades. Therefore, it is becoming more and more labour-intensive and time-consuming for manual interpretation on every line and time slice in a seismic cube. To resolve such limitation, great efforts have been devoted into automatic/semi-automatic seismic object detection.

By treating 3D seismic data as a suite of 2D images, various approaches have been introduced from the field of image/video processing to extract the target seismic features observed in the seismic images, and those approaches could be further divided into two subcategories, image segmentation and machine learning-based classification. Take the saltbody detection for example. The former is based on a single attribute, which is capable of clearly differentiating the salt from the non-salt features. For example, the normalized cuts image segmentation (e.g., Lomask et al., 2007; Shi and Malik, 2000) is applied to the discontinuity attribute and detects salt domes by solving a global optimization problem. The active-contour-models method (e.g., Zhang and Halpert, 2012; Haukas et al., 2013; Shafiq et al., 2015) starts with the initial boundary from interpreters and then gradually deform it to fit the attribute image. Wu (2016) presents the salt likelihood attribute and incorporates discrete interpreter picking into the detection process to guide accurate delineation of salt boundaries, especially in complicated zones with gaps or outliers. The latter takes into account the insufficiency of a single attribute to reliable feature interpretation, and integrates multiple attributes through machine learning-based techniques for improved detection accuracy and efficiency (e.g., Barnes and Laughlin, 2002; Zheng et al., 2014; Zhao et al., 2015; Di et al., 2017). However, there exist a number of different classification algorithms with varying terminologies, principles and complexities, which may bewilder the interpreters for selecting/configuring the most optimal algorithm for their work. In addition, these algorithms are often implemented and investigated through applications to different seismic datasets, and few papers have applied them to the same seismic dataset for fair comparisons.

In this paper, we first implement six commonly-used classification techniques for salt-boundary detection, including the logistic regression, decision tree, random forest, support vector machine, artificial neural network, and k-means clustering. Then twelve seismic attributes are selected for training classification models and detecting the salt boundaries from the F3 seismic dataset of multiple salt domes over the Netherlands North Sea. The good match between the detected salt boundaries and the original seismic images indicates that based on well-selected attributes, all six classification techniques are capable of providing reliable salt detection from 3D seismic data to assist structural framework modelling in the presence of salt domes.

Attribute selection

For efficient salt-boundary delineation, the selected attributes are expected to enhance the salt boundaries more distinguishable, whereas the non-boundary features (such as horizons) are significantly suppressed or even eliminated in the attribute images. Among all possible seismic attributes, we select and generate twelve attributes from the amplitude volume (Figure 1), including RMS amplitude, GLCM texture (e.g., Gao, 2003; Eichkitz et al., 2013; Di and Gao, 2016), Gradient of textures (GoT) (Wang et al., 2015), Seismic saliency (Shafiq et al., 2016), and Canny edge detection (Di and Gao, 2014), all of which differentiate the salt boundaries from the non-boundary features in different ways. To be clear, all the selected attributes are normalized before feeding to the classification algorithms, due to their different units of measurement and moreover distinct histograms.

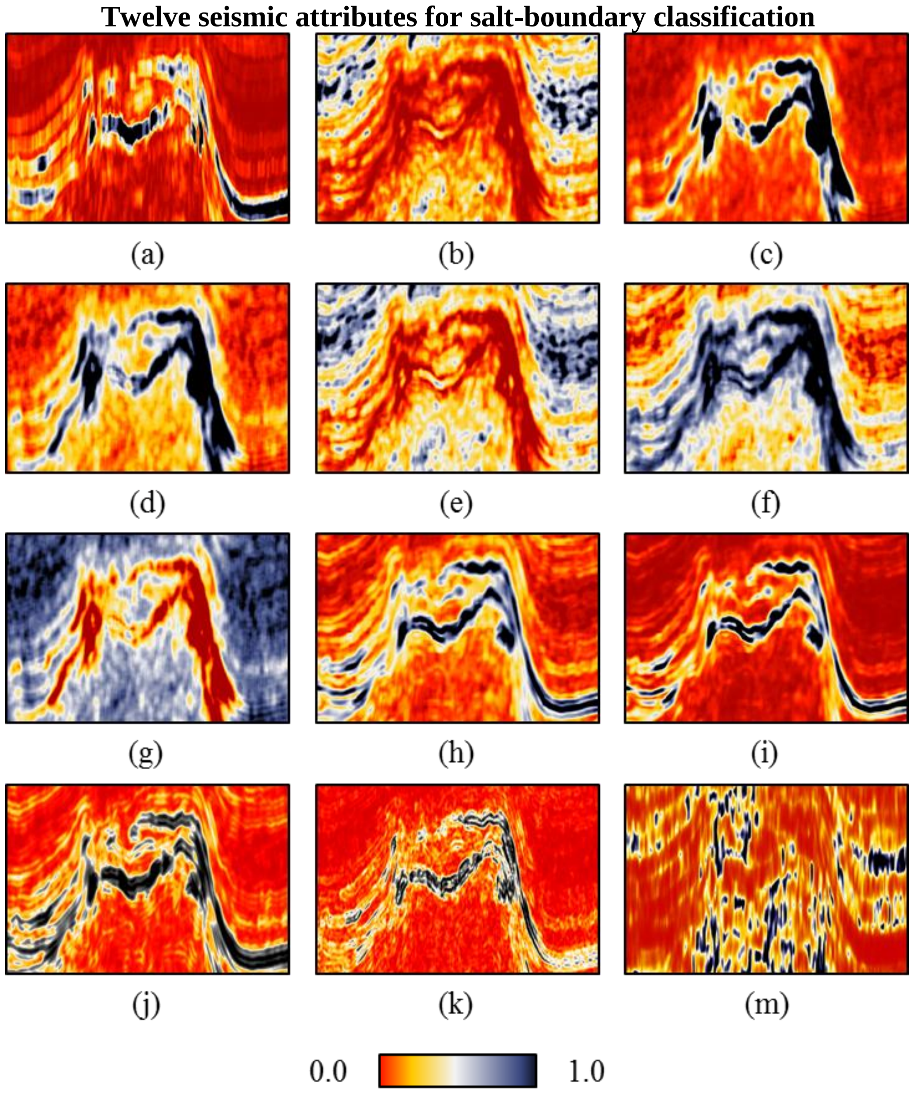

Figure 1 *The selected twelve seismic attributes used for multi-attribute salt-boundary classification, including (a) RMS amplitude, (b) GLCM angular second moment, (c) GLCM contrast, (d) GLCM dissimilarity, (e) GLCM energy, (f) GLCM entropy, (g) GLCM homogeneity, (h) GLCM standard deviation, (i) GLCM variance, (j) Gradient of Textures (GoT), (k) Seismic saliency, and (m) Canny edge detection. All attributes are normalized after generation.*

Results

Based on the twelve attribute, we apply six commonly-used classification techniques to a subset of the F3 seismic volume over the Netherlands North Sea for testing their performance on salt-boundary detection. Figure 2 displays the salt-boundary probability overlaying the seismic amplitude in 3D space, and we notice good match between the detection and the original seismic images, which indicates the accuracy of salt detection by the proposed multi-attribute classification. In addition, the similar results between all six algorithms demonstrate less sensitivity of seismic feature classification to algorithm complexities, compared to attribute selection and model training.

Besides the qualitative detection of the salt boundaries (Figure 2), the salt-boundary probability also makes it possible for quantitative interpretation, such as salt surface extraction by fitting a surface to the local maximums of the salt-boundary probabilities. Figure 3 displays the clipping of the extracted salt surfaces by the six classifications algorithms to two randomly-selected vertical sections, in which subtle misfits are observed between the curves and the salt-dome boundaries.

Salt-boundary probability

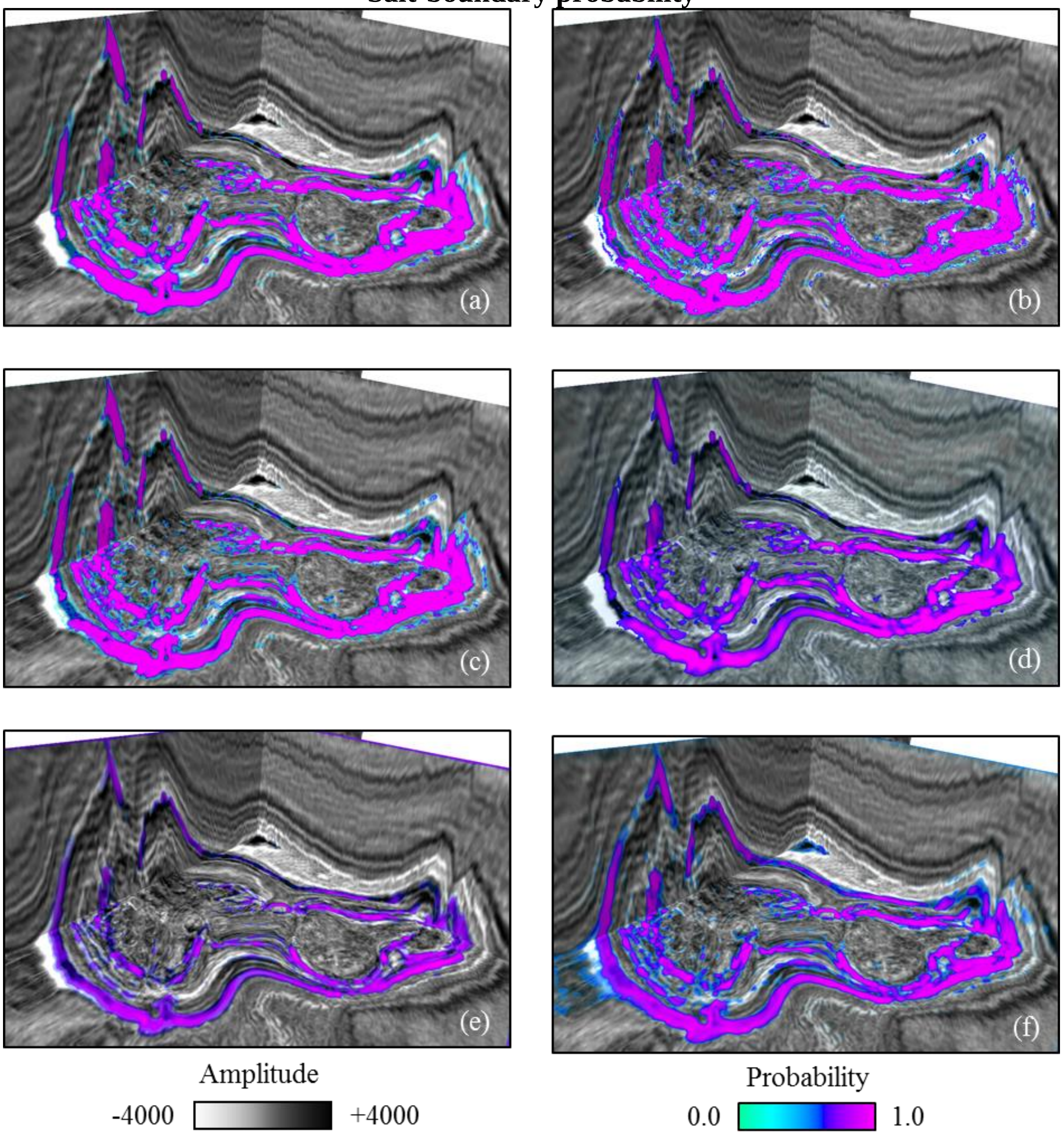

Figure 2 *The salt-boundary probability volumes from six classification techniques, overlaying the original seismic amplitude, including (a) logistic regression, (b) decision tree, (c) random forest, (d) support vector machine, (e) artificial neural network, and (f) k-mean clustering.*

Salt surface extraction

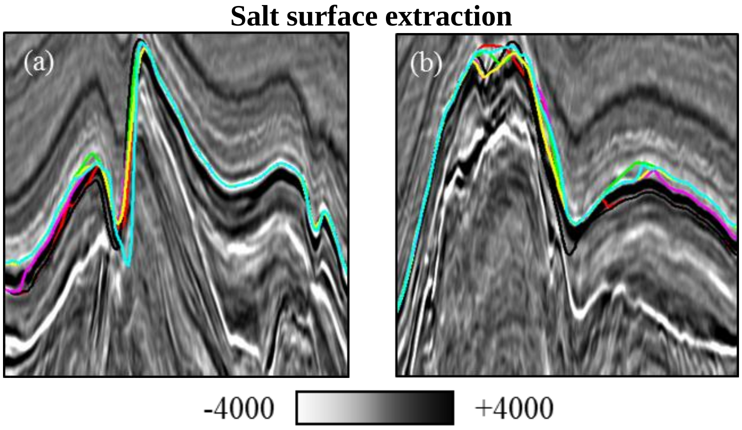

Figure 3 *The extracted salt surfaces from six classification techniques, clipped to two vertical sections, with the logistic regression in red, the decision tree in magenta, the random forest in black, the support vector machine in yellow, the artificial neural network in green, and the k-means clustering in cyan.*

Conclusions

In this paper, we have compared six commonly-used classification techniques for multi-attribute salt-boundary detection from 3D seismic data, including logistic regression, decision tree, random forest, support vector machine, artificial neural network, and k-means clustering. Twelve seismic attributes are selected for the salt-boundary classification, including RMS amplitude, GLCM texture, gradient of textures (GoT) and Seismic saliency. Applications to the F3 bock over the Netherland North Sea help verify the capabilities of the six classification techniques on reliable salt-boundary detection and their potential for efficient structural framework modelling in the presence of salt domes. Additionally, the similar results from different techniques indicate that, such classification is more sensitive to the seismic attributes, compared to the classification algorithms.

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