AI-driven interpretation of mega seismic surveys for strike-slip faults and salt-related structures in Abu Dhabi

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Summary

We present AI-drive workflow for automatic interpretation of large seismic volumes. The workflow is applied to an offshore Abu Dhabi area of 15000 km2. First, we show the fault detection results for the low-magnitude faults of strike-slip type by the fine-tuning of the DNN. The fault detection is conducted in a comprehensive way with structure-enhancing denoise for feature preservation. Second, we illustrate that automated horizon interpretation and flattening allows us to observe a variety of geological features, which are difficult to target otherwise. Finally, we show how the structure-enhancing denoise improves the geological feature identification by an example of channel detection. We further plan to apply the suggested workflow for a larger data set covering the whole Abu Dhabi offshore region.

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Introduction

Subsurface geological interpretation is an essential instrument employed for the exploration of hydrocarbon resources and the enhancement of established hydrocarbon reserves. Seismic data is key information of the structure of the subsurface, but the interpretation of seismic data is a time-consuming and human-dependent process, prone to bias and subjectivity. Modern imaging techniques make it possible to produce seismic volumes of high quality, covering vast areas of the subsurface with high resolution. Such data takes terabytes of memory storage and may contain a lot of important and detailed geological features. AI- and ML-based technologies are apt to be sensible solutions for extracting such information and can handle big data. We propose an automated workflow based on deep neural networks (DNNs). The workflow takes three stages with three corresponding DNNs: structure-enhancing seismic denoising and fault detection, seismic horizon interpretation, and channel detection.

We apply our workflow to a survey covering 15,000 km² near Abu Dhabi. The input seismic data is a 1 Tb post-migration cube in time domain. The region contains different varieties of geological objects, such as faults of various regimes, karst, salt bodies, channels, and clinoforms. The case study application of our workflow shows the following: First, we show the fault detection results for the low-magnitude faults of strike-slip type by the fine-tuning of the DNN. The fault detection is conducted in a comprehensive way with structure-enhancing denoise for feature preservation. Second, we illustrate that automated horizon interpretation and flattening allows us to observe a variety of geological features, which are difficult to target otherwise. Finally, we show how the structure-enhancing denoise improves the geological feature identification by an example of channel detection.

Method

The structure-enhancing denoise and fault detection are two processes that we consider in a comprehensive way. Faults are one of the most visible geological structures and can be interpreted by identifying shifts and discontinuities of seismic events. Thus, the sharpness of the image quality around the faults must be maintained during denoising. The simultaneous seismic denoise and fault detection can preserve and enhance such structures. The DNN model we use is a customized 3D UNet (Wu et al., 2019) trained on synthetic data in a supervised manner. The input data is a raw seismic cube, and the output is the denoised seismic and the fault probability volumes. We generate the synthetic data similarly to Wu et al. (2020). For synthetics, we create realistic 3D geological structures, parameterized by folding and physics-constrained faults. Then, we generate seismic reflection coefficients, interpolate along the geological structures, and convolve with various types of wavelets. The synthetic models contain seismic and the resulting fault volume. To train the DNN for seismic denoising, we combine the fault volume and corresponding seismic to provide feature preservation.

To address the low-magnitude faults of transform type, we train the DNN model for fault detection in two stages. First, we train a generalized DNN using variations of all possible fault types in a physically meaningful range. In the second stage, we fine-tune it by generating the bespoke synthetic data. The bespoke synthetics mimic the tectonic regime of the Abu-Dhabi region. The second stage is necessary because the fault types in the region are often transform-like, narrow (comparable to the horizontal sampling step), and have a small slip along the fault surface. Such fault types are often non-visible in a vertical section and can be traced only on the horizontal slices after the seismic denoising. To provide the detectability of such fault structures, we generate synthetics with narrow fault planes, strike-slip mechanism, and slip values comparable to the vertical sampling of seismic.

For automatic horizon interpretation and seismic flattening, we use the concept from Lomask et al. (2006). The method is based on dip-inversion, which allows for recovery of equally sampled horizon surfaces along the vertical axis and relies on a highly detailed dip volume derived from the seismic. The dips can be inverted using fine, coarse, or a combination of multi-scale grids.

Many of the channel structures are more obvious to observe after volume flattening and easier to detect after structure-enhancing denoising is applied. The channel detection DNN model is a customized 2D UNet (Ronneberger et al., 2015). The input data is the seismic data after denoising and flattening. The output is the probability value of channel detection in the range from zero to one. In the data set, we consider the channels to rarely be thicker than a few vertical samples, though the morphology is often very interpretable and complex. We deliberately use the 2D detection model, as it makes the DNN model converge faster while training and makes it more robust. The training data is a combination of the horizontal slices of a real seismic volume with the synthetically generated channel systems. A similar approach for channel detection is shown by Pham et al. (2019).

Results

Figure 1 shows the comparison of fault detection between pretrained (Figure 1a) and fine-tuned (Figure 1b) DNN models using a specifically designed training data set. The faults in this region are mostly sub-vertical with a strike-slip type of movement and small magnitude (shift along the fault is smaller than half of a period of a seismic event). One can see in Figure 1 that the DNN model provides a very fine and detailed detection of the fault structures. The 3D approach for the detection is important, as, in many cases, the fault cannot be seen by observing only the 2D section. On the other hand, the horizontal slice shows obvious structural consistency.

The results of the fault detection are collateral within the study from Noufal et al. (2016), but utilize only seismic data, whereas previous research is based on a set of different data types (gravity, magnetic, and seismic). The DNN detects different fault types, including large blocks of strike-slip and dip-slip. Some areas are more complicated due to salt-related structures and unconformities. The Figures 1b and d robustly highlight the fault-related discontinuities. For some areas, the human interpretation and validation is required to decide how the detected faults should be connected into a single plane.

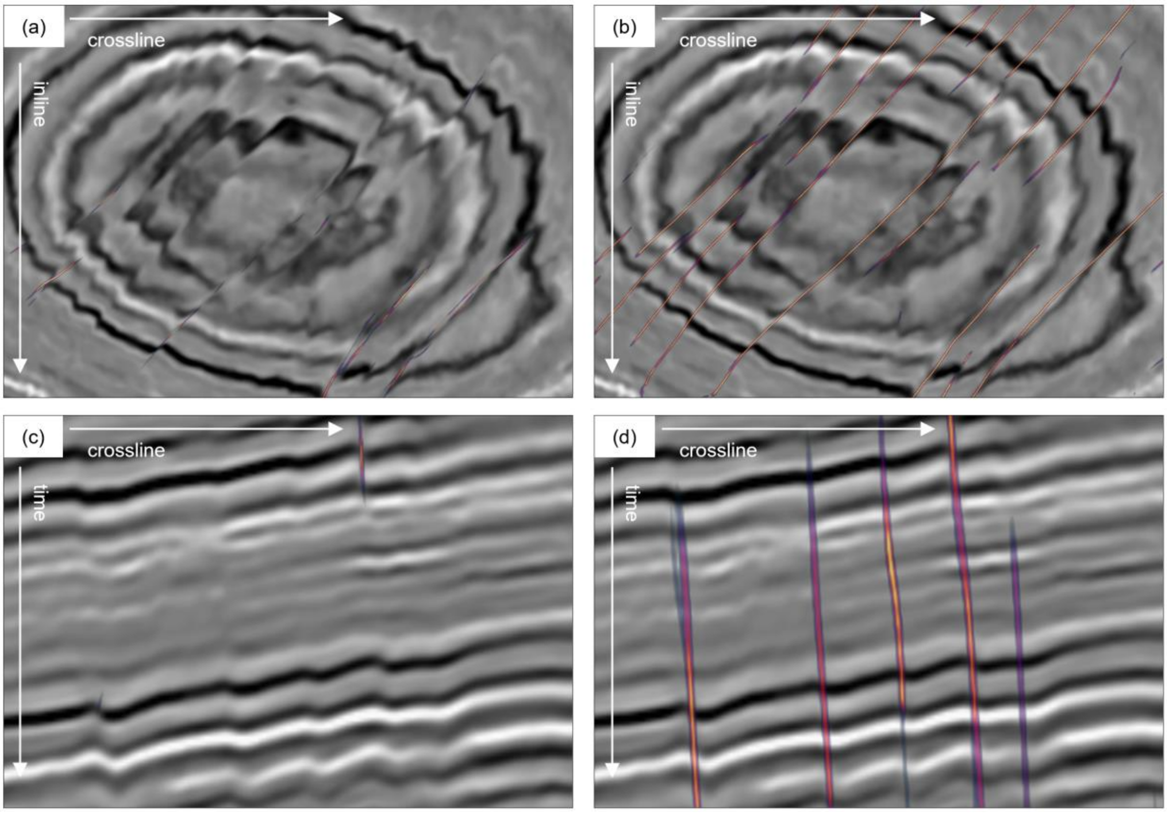

Figure 1 *Fine-tuning of automatic AI-driven fault detection. (a) and (b) show horizontal time slices of a seismic volume overlapped with fault detection probability; (c) and (d) show cross-section examples. (a) and (c) – fault detection results before fine-tuning; (b) and (d) – after. Probability value colormap in a range from zero to one, changing from deep purple to gold colour.*

Figure 2a illustrates results of the automated horizon interpretation from a subset of the mega survey – a scene of inline and crossline sections with automatically detected horizons. The presented seismic is after the structure-enhancing denoise. Our dip-based inversion algorithm enables high-resolution horizon picking on a fine grid. This technique is crucial to calculating a flattened seismic volume, also known as the stratigraphic volume or stratal domain. In Figures 2b, c, and d, we present time slices, while Figures 2e, f, and g showcase the corresponding stratal slices. One can see that the stratal slices offer a more distinct and detailed view of geological features (channels, faults, and karst).

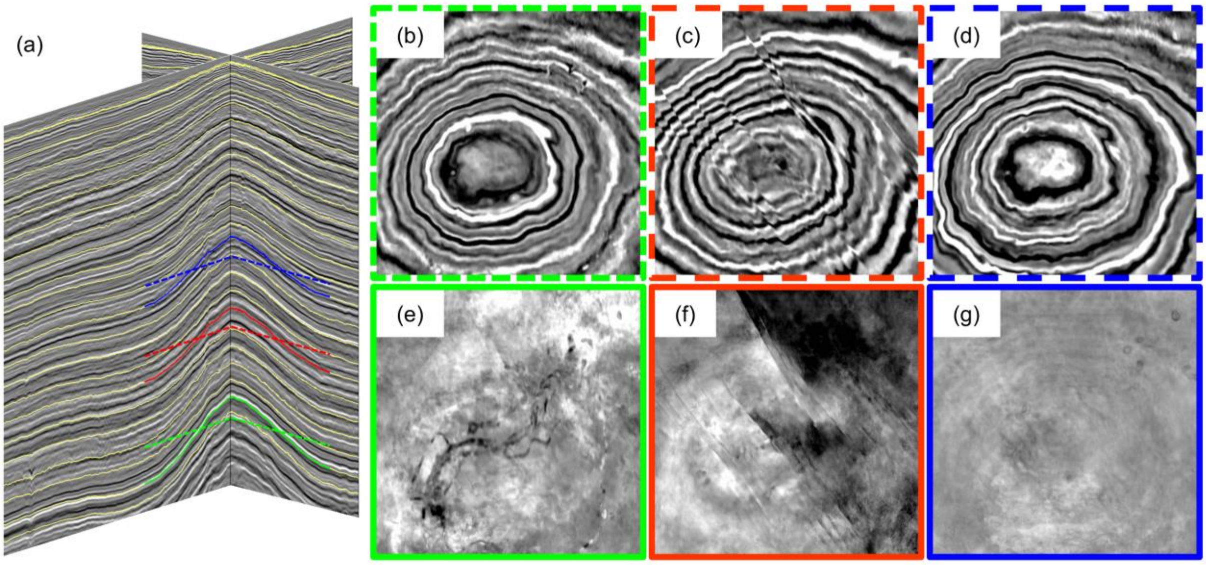

Figure 2 *AI-driven automatic horizon interpretation. (a) seismic volume overlaid with automatically detected horizons: yellow – example horizons; red, green, and blue – horizons selected to compare stratal- and time-slices; dashed lines – location of time slices. (b), (c) and (d) show seismic amplitude extracted from corresponding time slices. (e), (f) and (g) show the seismic amplitudes extracted along the automatically interpreted horizons (stratal slices).*

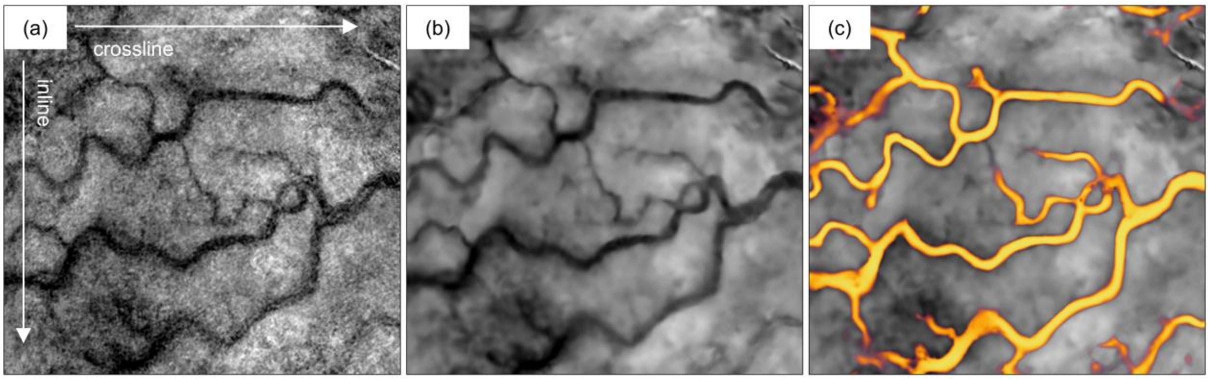

Figure 3 *AI-driven automatic detection of channels: horizontal slice of a raw seismic volume (a) after flattening, (b) after structure-enhancing denoise, (c) probability of channel detection overlapped on top of seismic slice. Probability value colormap in a range from zero to one changing from deep purple to gold colour.*

In Figure 3, we show the channel detection result. The channel detection is done slice-by-slice in a 2D sense. The denoising results (Figure 3b) show efficient removal of the un-structured noise, preserving the edges of the channel structures. This helps to increase the robustness of the DNN for channel detection. We deliberately illustrate the denoising effect by application to channel detection, as it is the domain where the importance of structure enhancement is highlighted. Out internal tests show that similar preconditioning is suitable for detecting other objects like karst as well. A different DNN can be trained for karst detection, considering that these objects tend to be small (about 50-100 m in diameter). One can use methodology from Sancheti and Hou (2023) to prepare the synthetic data set and train the karst detection DNN. The channel structure for this data set is ambiguous, as the seismic is contaminated by noise and residual multiples and complicated by geological unconformities. However, one can see that most branches of a channel system are detected.

Discussion

We have developed an automatic AI-based workflow to reveal the geological insights of a mega seismic survey of 15,000 km^2 with a seismic cube size of 1 Tb. The workflow utilizes three DNN models to deliver denoised seismic and faults, horizons, and channels. The consumed resources for the automatic workflow are incomparably small relative to the human-driven or semi-automatic flows. We aim to conduct a global regional solution with less human effort. The challenging areas (e.g., densely faulted areas, salt dome slopes, poor event continuity) will require human validation and post-processing. First, we showed the fault detection results after creating the bespoke synthetic data to fine-tune the DNN model to target the narrow, strike-slip faults of low magnitude of a slip. We showed that the fine-tuned model detects the fault structures, which coincides with the previous geological studies. Second, the automated horizon interpretation and flattening allows us to observe features like channels and karst. Finally, we presented the channel detection after structure-enhancing denoise and flattening.

The key challenge for this study is the multiple contamination. The water bottom is relatively shallow and flat, which makes it difficult to remove multiples. As a result, the stacked volume contains a significant phase-tuning effect. The misalignment of the phases along a seismic event makes the horizon interpretation results dependent on the chosen frequency band. Despite currently utilizing the DNN-guided denoise, it is still a struggle to target the residual multiples. The improved demultiple and advanced imaging techniques may further improve horizon interpretation and subsequent detection of channels, karst, and other geological features. We further plan to apply the suggested workflow for a larger data set covering the whole Abu Dhabi offshore region.

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