A generalized U-Net for injectite detection

O. Sancheti[1], S. Hou[1]

[1] CGG

Summary

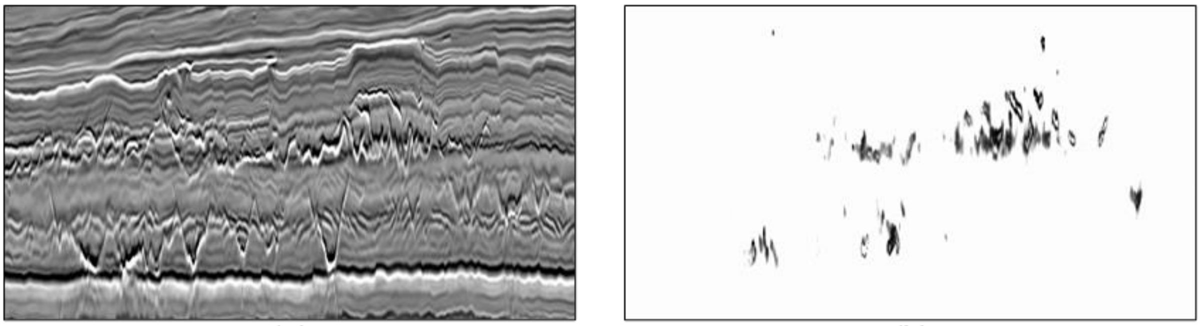
Geological bodies like sand injectites are found in numerous geodynamic and geological contexts around the world, and they can manifest as low- or high-amplitude seismic responses with complex structures.
In this paper, we demonstrated an amplitude preserving DNN-based workflow for injectite detection using customized U-Net. Our workflow addresses the challenges inherent in the limited number of training datasets and produces a pretrained model that delineates injectite events on migrated seismic images. To address the issue of domain shifting, we proposed a transfer learning approach that avoids mis-predicting faults and other diffraction events as injectites. Finally, we discussed how this result could benefit the seismic processing workflow.

A generalized U-Net for injectite detection

Introduction

Geological bodies like sand injectites are found in numerous geodynamic and geological contexts around the world, and they can manifest as low- or high-amplitude seismic responses with complex structures, as shown in Figure 1a. Injectites are created by fluidized sand being forcibly driven upwards into surrounding host rocks, resulting in the formation of dykes and sills (Hurst et al., 2003). Interpretation and insertion of injectites into the model can be a beneficial component of a velocity model building workflow. Defining their thickness, borders, and AVO is also important in order to calculate potential hydrocarbon volumes, develop plans for petroleum exploration and production, and enhance oil recovery. However, these geological bodies take on diverse and complex shapes that make seismic imaging and interpretation a challenging task. A traditional workflow for interpreting injectites requires a time-consuming collaborative effort between skilled geophysicists and geologists. The entire process can take weeks or even months, depending on the area size.

Applications of deep learning have brought about a revolution in various fields, including healthcare, natural language processing, and self-driving automobiles. Additionally, studies have shown the potential of using deep neural networks (DNNs) for detecting geological features, such as faults and salt bodies, on seismic images by treating this task as one of image segmentation. In other words, the DNN model takes a post-migration seismic image as input and predicts the binary masks of the target geological features or bodies. However, conventional DNN algorithms for image segmentation are not suitable for injectite detection. As shown in Figure 1b, a convention method failed to detect the weak injectites. There are three major reasons for this. First, the seismic responses of injectites are unique among geological bodies; injectite bodies are not only structurally complex but also thin. Because they are often overlaid with other strong reflections (Figure 1a), they are difficult to detect, even by human eyes. Therefore, it is difficult for DNN to detect injectites in addition to other geological bodies that are much larger and more obvious on seismic images, such as salt bodies. Second, training a generalized DNN model requires a large number of high-quality labels. For the same reason as above, it is time-consuming to manually pick accurate labels for injectites. Third, one of the main purposes of detecting injectites is reservoir characterization. This means we are not only interested in knowing their location (the binary mask in machine learning terminology) but also their true amplitude for AVO analysis, which cannot be provided by conventional DNN methods for image segmentation. To overcome these challenges, we developed an amplitude preserving DNN-based workflow to extract injectites and their seismic responses.



(a) (b)

***Figure 1**: (a) Migrated seismic image that contains injectites; (b) Binary mask of injectites predicted by a conventional U-Net method.*

Methodology

1. Dataset: In order to generate more training datasets from the limited number of manually picked injectites, we propose an approach of synthesising realistic training datasets. First, we collected a large number of 2D slices from 3D seismic images without injectites as the background. To make the model

generalise better, the background should cover various geological settings, seismic signatures, and signal-to-noise ratio (SNR) levels (see the samples 1 and 2 in in Figure 2a). Then, we created a 2D seismic image dictionary of manually interpreted injectites (Figure 2b). Finally, we randomly paired an image from the background and an image from the injectite dictionary and summed the two images to create the input of the DNN, as shown in Figure 2c. The target of the DNN is the 2D seismic image of injectites. This way, we obtained a large number of training datasets, covering a large variety of injectites and background geologies. 80% of these datasets were used for training and 20% for validation.

2. Model training and evaluation: We modified a tailored 2D U-Net (Ronneberger et al., 2015) for delineating injectites from input seismic images. The main changes are: (1) our model predicts the seismic images of injectite bodies rather than the binary masks, with pixels inside the injectites set to true and pixels of the background set to false, in order to preserve the true amplitude of the injectites' seismic responses; (2) consequently, we choose the mean squared error (MSE) loss instead of the binary cross entropy (BCE) loss.

We applied the pretrained model to test seismic data in the Norwegian North Sea. As shown in Figure 3, the model performed decently. It delineates not only strong seismic images of injectites but also subtle amplitude variations at the edge of each injectite body, which are missed by conventional U-Net approaches (Figure 1b).

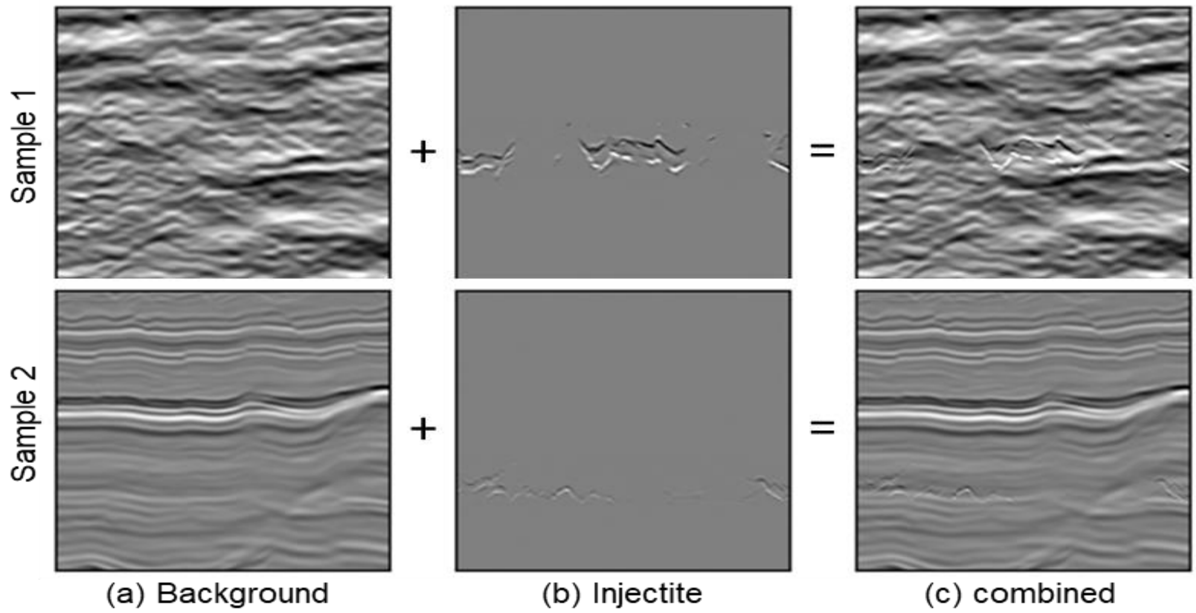


Figure 2*: (a) Injectite-free seismic image as the background; (b) Seismic image of injectites from manual interpretation; (c) combined seismic image of (a) and (b)*

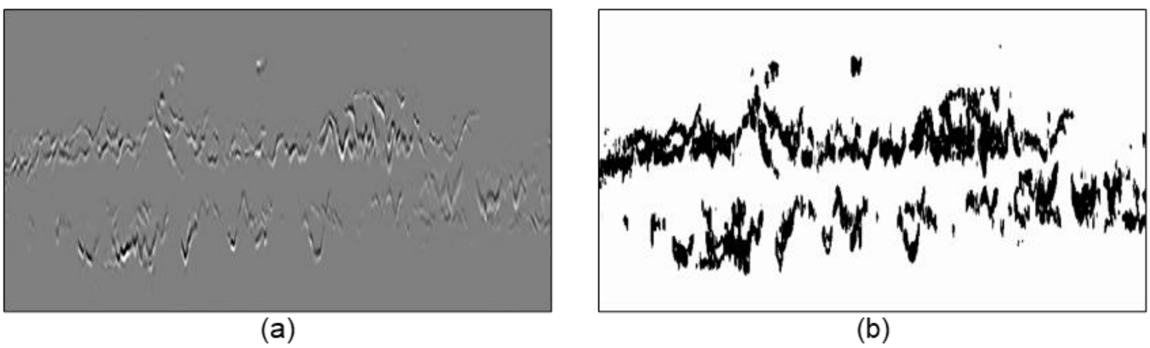


Figure 3*: (a) Seismic responses of injectites predicted by applying our U-Net to Figure 1a; (d) Binary mask derived from (a).*

However, after analyzing the results in greater detail at a regional scale, we observed that the model sometimes delineates reflections from the fault surfaces as injectites, i.e., false positives, as highlighted by the dashed boxes in Figure 4b. This is due to the "domain shifting" problem, in which the geology and/or seismic character of the test dataset are different from those of the training dataset. To improve accuracy and reduce the number of false positives, we applied transfer learning. Specifically, we created a new set of training datasets that includes the injectite-free data from the test area. We then fine-tuned the pretrained model with the new training datasets. This reduced the domain shift and, consequently, significantly reduced the false positives, as shown in Figure 4c.

3. Processing the 3D seismic volume via the 2D U-Net model: By combining the predicted injectites on each 2D section from the 3D seismic volume, we obtained the injectite bodies in 3D. Figure 5 shows 3D masks of the injectite bodies obtained by thresholding the seismic envelope of predicted 3D injectite bodies.

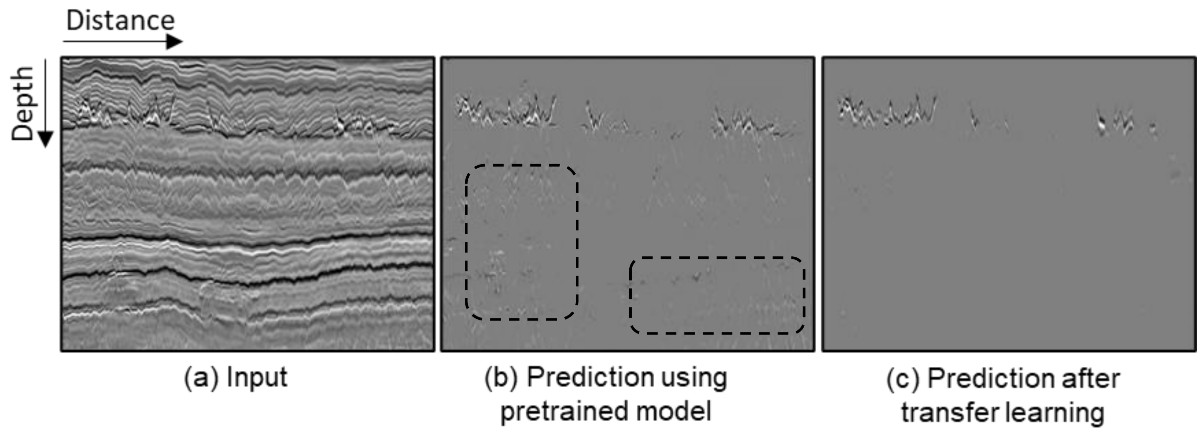


Figure 4*: (a) Input seismic to DNN model; (b) Predicted injectites using pretrained model; (c) Predicted injectites using the updated model with transfer learning.*

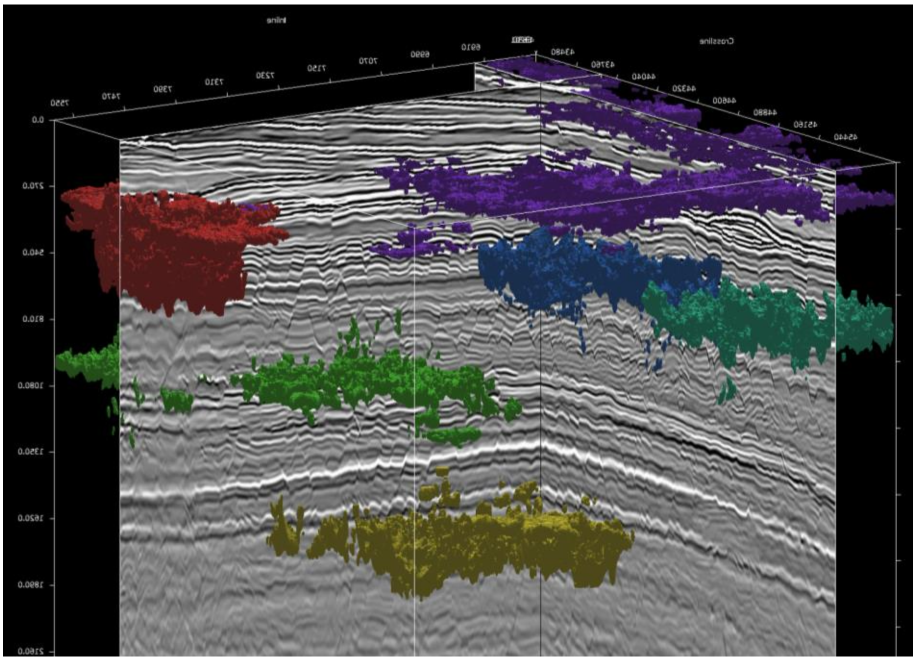


Figure 5*: 3D visualization of injectite masks*

Challenges and opportunities

Lack of training data is a common challenge in developing deep learning models in the geological domain. This is because it is often expensive and time-consuming to acquire such data. However, as discussed, our strategy of synthesizing realistic training data helped solve the problem of insufficient data; this, in turn, also helped the model to generalise well. One of the most prevalent challenges in real-world deep learning applications is domain shift. Since our model was trained on a particular volume of seismic data and applied to different volumes of real seismic data, domain shift exists in several aspects, such as wavelet, noise, and geological structure. For our problem, transfer learning reduced the effects of domain shift and improved model performance. The quality of seismic data also plays an important role in model performance. Figure 6 compares the results of our pretrained DNN model on vintage versus more recent seismic data. The model is not able to delineate injectites from the vintage seismic, while it performed well on the more recent seismic data. This shows that the quality of the seismic image has an important effect on the quality of the solution. We suggest future analysis on how model performance is impacted by the quality of seismic images, such as signal-to-noise ratio, frequency content, and resolution.

Another advantage of our DNN approach is its efficiency. We are able to delineate the injectite bodies within a few hours using GPU for inference, while it used to take days or weeks of manual interpretation. This provides the opportunity to use this information in the middle of a seismic processing project. For instance, the injectites are high-velocity sands trapped in thin layers and will not show up in a low-frequency starting velocity model built by tomography. Therefore, the DNN predicted injectites can be used as a priori information in early velocity model building stages that later goes into high-resolution full-waveform inversion.

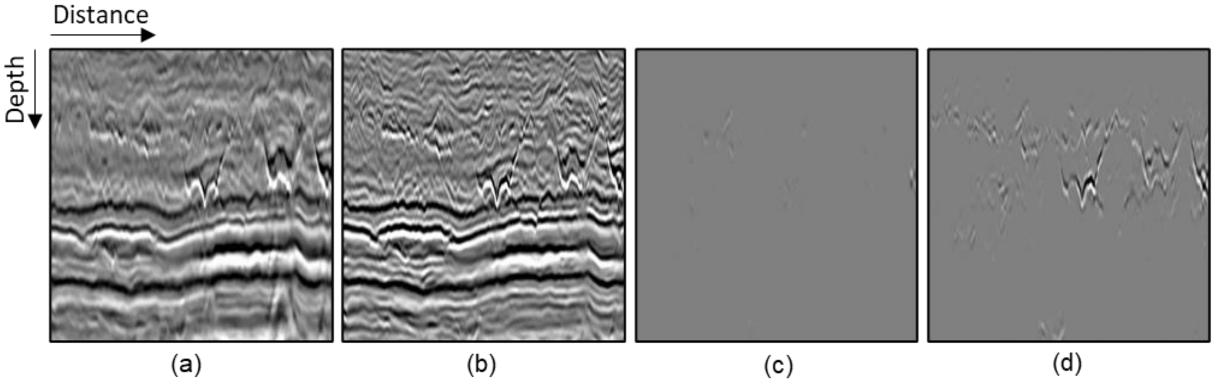


***Figure 6**: (a) Vintage seismic; (b) More recent seismic; (c) Model prediction from (a); (b) Model prediction from (b).*

Conclusions

We demonstrated an amplitude preserving DNN-based workflow for injectite detection using customized U-Net. Our workflow addresses the challenges inherent in the limited number of training datasets and producpes a pretrained model that delineates injectite events on migrated seismic images. To address the issue of domain shifting, we proposed a transfer learning approach that avoids mis-predicting faults and other diffraction events as injectites. Finally, we discussed how this result could benefit the seismic processing workflow.

References:

Hurst, A., Cartwright, J., Huuse, M., Jonk, R., Schwab, A., Duranti, D., & Cronin, B. [2003] Significance of large-scale sand injectites as long-term fluid conduits: evidence from seismic data. *Geofluids*, **3**(4), 263-274.

Ronneberger, O., Fischer, P., & Brox, T. [2015] U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, 234-241.