Deep Learning for Salt Body Detection: A Practical Approach

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Summary

Interpreting salt bodies in the subsurface is a challenging manual task that can take weeks to complete. Obtaining accurate picks of salt is very important, because errors in the placement of salt can result in severe degradation of the seismic image. To meet the challenges of speeding up imaging workflows and retaining accurate salt picks, we evaluate three deep learning approaches: a 2D window-based convolutional neural network, a 3D window-based convolutional neural network, and finally a 2D "U-Net" approach. A 3D seismic volume from the deep-water field Julia in the Gulf of Mexico was used to test these approaches. The Julia field has complex salt structures with overhangs and inclusions, and the thickness of salt can reach up to 5 km. The U-Net architecture proved to be the most accurate of the three methods tested, predicting the placement of salt at 98% accuracy, as compared to the human interpretation. Beyond accuracy, U-Net also proved to be the fastest, requiring only 3.5 hours to predict salt on the 3D seismic volume. The results presented here along with other recent studies of deep learning for salt interpretation represent a clear shift in the seismic interpretation workflow.

Introduction

Salt interpretation can be an arduous task that routinely takes weeks to accomplish on typical large 3D surveys when manual picking tools are used, which causes a bottleneck in the seismic imaging workflow. At the same time, the accuracy of the salt interpretation is critical, because errors in boundary interpretation can significantly damage sub-salt images, create false structure, and misplace dipping horizons. The challenge is magnified where salt boundaries are multi-valued, that is, where overhangs and inclusions are present.

Automatic interpretation of salt bodies in the subsurface has been a subject of interest in the oil and gas exploration industry, and recently, machine learning algorithms have been implemented for salt body segmentation (Guillen et al., 2015; Shafiq et al., 2017; Shi et al., 2018; Zeng et al., 2019). In general, image segmentation is the process of partitioning an image into several distinguished parts. In the case of salt body segmentation, the goal is to distinguish between *salt* and *not salt*. The recent advancement in deep learning algorithms has brought a promising outlook for applications in salt interpretation, along with many other image segmentation tasks (see for example, Duro et al., 2012). The aim of this study is to evaluate deep learning algorithms from a practical point of view: first, to obtain a highly accurate salt body prediction, and second, to significantly reduce the seismic interpretation turnaround time with an automated and computationally efficient workflow.

We evaluate three deep learning methods: a 2D window-based convolutional neural network, a 3D window-based convolutional neural network, and a 2D "U-Net" architecture (Ronneberger et al., 2015). We illustrate the fidelity of these methods with images from an ocean bottom node survey at the Julia field in the deep-water Gulf of Mexico, where a massive allochthonous salt overlays a deep sub-salt reservoir.

Methods

Most classic supervised machine learning based algorithms can utilize and parse a certain number of attributes to predict the desired output. In this paper, we use binary classification to distinguish between salt and other sediment types. Among various machine learning techniques, artificial neural networks are the most popular, owing to their variable forms of network architecture. For example, deep neural networks, or multi-layer perceptron, consist of multi-layers of fully connected neurons, and fundamentally rely on a set of attributes (for example, edge, sharpness, amplitude, etc.) being provided as inputs. Convolutional neural networks (CNNs), however, have given rise to exceptional accuracy in image classification and segmentation, in which the network itself generates the required attributes via multi-convolutional layers acting as filters on the image. CNNs also have multi-layer neurons, similar to deep networks, and are the focus of this paper.

There are two main approaches to implement convolutional kernels for salt body segmentation. The first and perhaps the most straightforward approach is by feeding many small patches of seismic data in a 2D or 3D fashion (Zabihi Naeini and Di, 2018) into a CNN. In this paper, we refer to this method as a window-based CNN. The second approach is based on a U-Net architecture (Ronneberger et al., 2015). The window-based CNN and the U-Net architecture are schematically shown in Figure 1. The U-Net consists of contracting and expanding branches, each of which can be akin to a typical CNN architecture. However, one defining characteristic of a U-Net architecture is that the expanding branch of the network is informed not only by the previous layers, but also by the matching sized contracted branch (see black arrows). U-Net optimally recovers both the context and resolution of the salt bodies compared to the window-based CNN. Another key differentiating element between sliding window-based CNNs and U-Net is the output layer. In U-Net, the output is the same size and shape as the input image with classified segments (here salt and non-salt); however, a window-based CNN classifies each patch independently. Based on Figure 1, for a seismic image of size 1465 traces by 1601 samples, classification is performed on 2,345,465 samples. In practice, a window-based CNN requires much more computational time than a U-Net architecture. Further details of the computational differences are discussed in the case study below.

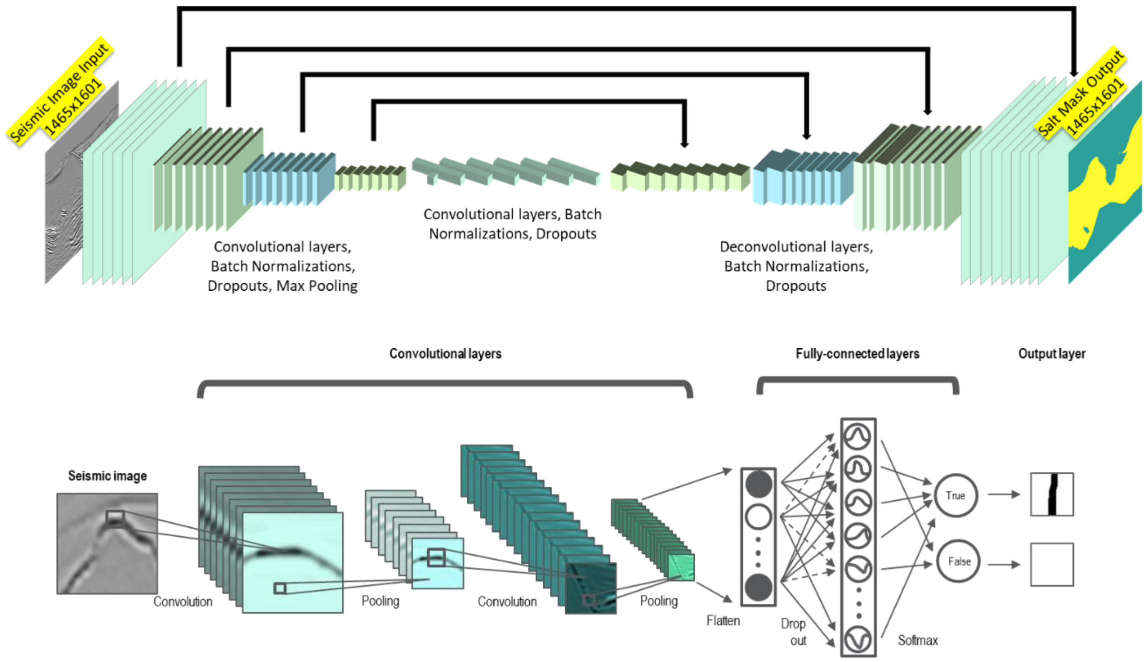

Figure 1 *U-Net (top) versus window-based CNN (bottom) architectures implemented for salt body segmentation (figure modified from Zabihi Naeini and Di, 2018).*

Case Study

In this section we analyze the performance of the CNN window-based approach and U-Net (Figure 1) on a 3D seismic volume from the Julia field in the Gulf of Mexico. Julia is situated about 425 km southwest of New Orleans in water depths of around 2200 m. The reservoir formations lie 6.4-7 km below seabed. The salt at Julia is massive – 5 km thick in places – and complex: the two salt tops, two salt bases, plus some inclusions, would take approximately three weeks to interpret manually.

Training for the Julia data was performed using five randomly selected inlines and the networks' performance were optimized on two validation inlines. The idea behind selecting only five inlines is to avoid requiring too much time for manual interpretation during the training process. The accuracy is measured on one test inline, where U-Net achieved 98% accuracy and the 2D window-based CNN achieved 94% accuracy. One could extend the sliding window-based CNN to 3D where 3D mini cubes are fed instead of 2D patches as shown in Figure 1. The 3D algorithm only improves the performance marginally by 1.2%, that is, to 95.2%. It is possible that with more training epochs, the 2D and 3D CNN algorithms could become more accurate, but because U-Net was outperforming the window-based CNN approaches, there was little reason to continue testing the window-based approaches any further.

There is a significant difference in computational time between the window-based CNN and U-Net for predicting the final 3D volume. The dimensions used for model prediction were 352 inlines (every 4th inline), 1465 crosslines and 1601 samples. U-Net predicted the volume in 3.5 hours, the 2D window-based CNN in 21 hours, and the 3D window-based CNN in 44 hours. Each test was performed on a single 12GB NVIDIA Tesla K80 GPU, courtesy of Google Colab. U-Net outperforms window-based algorithms both in terms of accuracy and computational time. The computation time required for U-Net to predict 352 inlines can be further reduced to only 1 minute with more advanced GPUs, such as the 16GB Tesla P100.

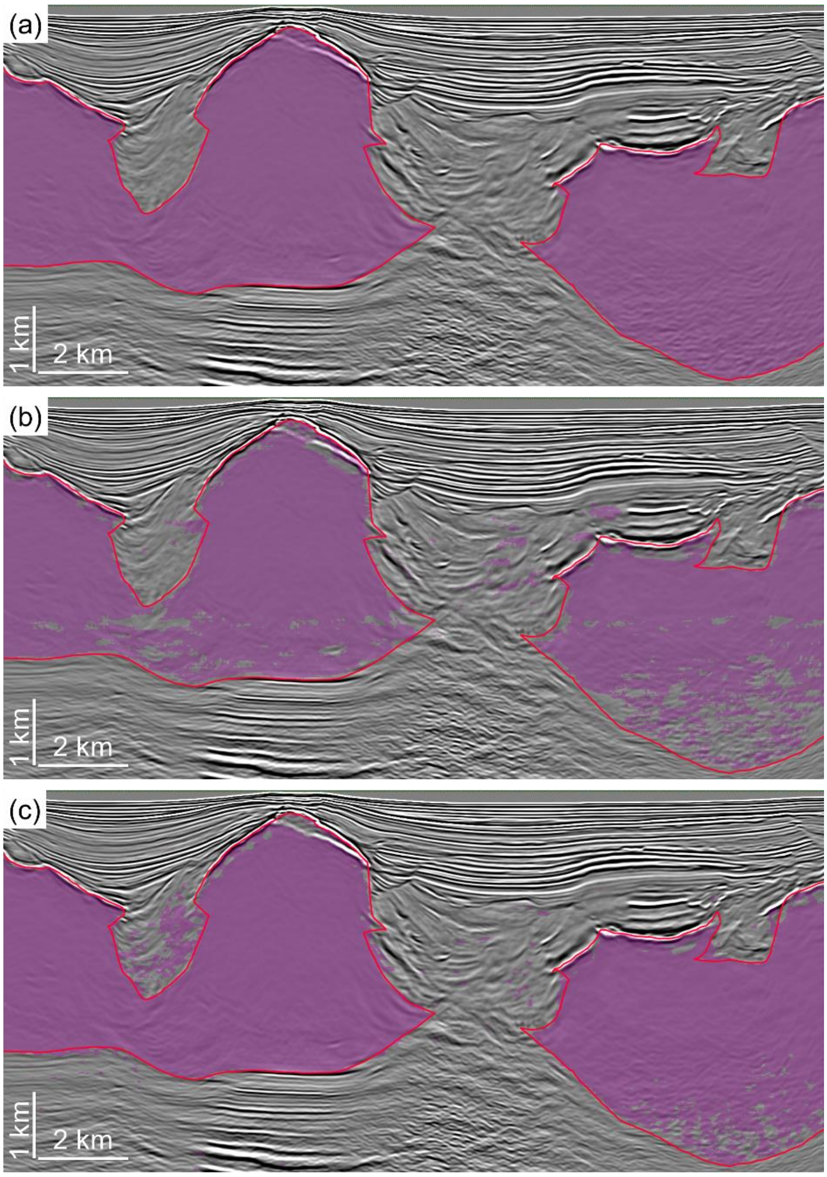

Figure 2 *A 2D view of a test inline comparing U-Net (a) versus window-based CNN architectures using 2D (b) and 3D (c) kernels for salt body segmentation. The red lines indicate manual interpretation, and purple is the segmented output.*

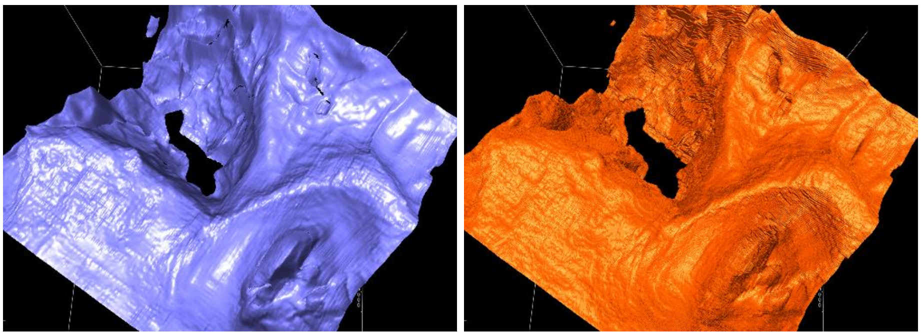

Figure 3 *A 3D map view of top of the salt surface manually picked (left) versus U-Net (right).*

Figure 2 illustrates a blind inline comparison between the U-Net and window-based algorithms. The U-Net prediction visually matches much more closely to the manual picks (red) than the window-based CNN prediction. Figure 3 shows the manually picked salt top (left) versus the U-Net predicted salt top (right). The high accuracy of the U-Net prediction, along with the workflow time reduction, provide significant uplift in any salt picking project. For the example shown in this paper, turnaround time is reduced from 3-4 weeks to 3-4 hours.

Finally, it is worth pointing out that a typical salt interpretation with depth imaging workflow combines numerous iterations of salt picking and imaging, as salt tops and bases come into focus and are placed into an evolving velocity model. Our example uses a final depth migrated image from which an entire salt boundary is interpreted in one step. Thus, it still needs to be demonstrated that machine learning for salt interpretation can be inserted effectively into the iterative depth imaging workflow, and this is our current area of focus.

Conclusions

The U-Net architecture outperformed the 2D and 3D window-based CNN architectures in both accuracy and speed on the Julia salt dataset. The U-Net approach achieved 98% accuracy on salt body detection, whereas the 2D and 3D window-based CNN approaches achieved 94% and 95%, respectively. The 2D and 3D CNNs took 21 hours and 44 hours for prediction, whereas the U-Net took only 3.5 hours for prediction. Interpreting the salt bodies manually took 3-4 weeks on the Julia data. The speed and accuracy of the U-Net approach gives clear motivation to use it to accelerate the salt interpretation workflow. The method has now also been successfully tested on another 3D offshore dataset from the Gulf of Mexico, with similar results in time and accuracy. One limitation is that the deep learning approach does not perfectly estimate salt, and there are some areas that would need to be edited manually by an experienced seismic interpreter. However, the time savings by using deep learning are still significant and such interaction between the practitioner and the machine can be performed interactively on the fly.

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