Implementation of Seismic Salt Interpretation by a Deep Neural Network with Neural Style Transfer

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Abstract

Objectives
Recently, machine learning (ML) approaches show promising ways to delineate subsurface features. However, due to the non-unique nature of seismic data and domain discrepancy, seismic interpretation, especially salt interpretation, has limited resolution and heavily relies upon an interpreter's experience with a limited set of geological concepts. Seismic data acquired from different surveys also show various features due to deposition environments and surrounding phenomena. Those geological environments will significantly affect the accuracy of the ML model. In this abstract, we propose a new architecture by implementing an Xception-backed encoder-decoder network, to train a model for salt prediction. The training data is optimized by deep learning Neural Style Transfer (NST), to minimize domain discrepancy by teaching synthetic data to learn features from field data as well as keeping the training label unchanged. Our method provides better generalization.

Procedures
We consider the SEAM data as synthetic training data, and field data from the Gulf of Mexico as the testing data. After properly configuring the network, we create Neural-Transferred Training Data (NTTD) which has similar content and style by teaching the NST model to obtain perceptual information from the synthetic training data and field data. The architecture is composed of a content reconstruction block and a style reconstruction block. We transfer data features from field data to synthetic training data to create the NTTD. The NTTD and labels are then input to a proposed Xception-backed encoder-decoder network to learn the mapping between the NTTD and labels. Xception was developed following a famous architecture Inception by Google. In this architecture, Xception composes a pointwise convolution followed by a depthwise convolution.

Results
The newly created NTTD data contains the original SEAM data features and also includes features from field data in the Gulf of Mexico. We use this new data to train an ML model built by the Xception-backed encoder-decoder network. Compared with the traditional U-Net model, The training workflow shows faster convergence, and the prediction result shows higher accuracy with fewer false positives. We observe that the NTTD data helps the model to learn more features from field data, it provides a good opportunity to apply this scheme to other interpretation projects.

Conclusions
Our proposed approach includes a neural style transfer workflow to combine features from field data with synthetic data to reduce domain discrepancy. With the implementation of the Xception-backed encoder-decoder architecture, we improve the accuracy to learn the mapping between the NTTD and labels. We believe that by introducing seismic features from field data to synthetic data, we could reduce the domain discrepancy and provide a solution to a generalization problem in salt interpretation.