Implementation of neural style transfer to mitigate domain discrepancy in the deep learning salt interpretation

F. Jiang[1], K. Osypov

[1] Halliburton Landmark

Summary

One of the significant challenges in seismic interpretation is to accurately delineate subsurface features and quantify the interpretation results. However, the success heavily depends on the quality and resolution of seismic data and the validity of assumptions on the stationarity of geologic representations. This challenge is analogous to human interpretation uncertainty, in particular when a geological concept developed for interpreting one seismic area does not work for another seismic volume due to changes in depositional environments or changes in seismic acquisitions. In this paper, we propose a new architecture by implementing neural style transfer and an Xception-backed encoder-decoder network to train a model for salt segmentation. The synthetic training data is optimized by deep neural style transfer to mitigate domain discrepancy and learn features from field testing data but keep the training label unchanged. Our experiments show that introducing features from field testing data into synthetic training data will significantly mitigate domain discrepancy and provide better prediction results.

Implementation of neural style transfer to mitigate domain discrepancy in the deep learning salt interpretation

Introduction

Recently, machine learning (ML) approaches have been showing promising ways to delineate subsurface features. However, the success heavily depends on the quality and resolution of seismic data and the validity of assumptions on the stationarity of geologic representations. Both issues are related to a domain discrepancy challenge for ML. This challenge is analogous to human interpretation uncertainty, in particular when a geological concept developed for interpreting one seismic area does not work for another seismic volume due to changes in depositional environments or changes in seismic acquisitions. In other words, learning (both human and machine) done for one seismic volume and related specific geologic features cannot be transferred to another volume with a different resolution or different geology. In this paper, we focus on the domain discrepancy associated with the non-stationarity of seismic data.

In computer vision, Neural Style Transfer (NST) refers to a technique that implements a pre-trained neural network with added loss functions to transfer style from one image to another and synthesize a newly generated image with the features we want to add (Gatys et al., 2015). In seismic interpretation, Ovcharenko et al., (2019) applied an iterative style transfer approach from image processing to produce realistically textured subsurface models based on a synthetic prior model. Park et al., (2022) proposed a workflow to incorporate real image features into synthetic images before training. Their results show that the updated synthetic images have similar characteristics to a real seismic image to achieve higher prediction accuracy.

Xception network stands for the extreme version of the Inception network. It shows good image processing and segmentation ability (Chollet, 2016). Xception includes a series of depthwise separable convolutions, which is composed of a pointwise convolution followed by a depthwise convolution. A pointwise convolution is designed to learn the relationship between spaces, as a depthwise convolution is designed to learn the relationship between channels. Compared with Inception and ImageNet, the Xception encoder-decoder network shows advantages in medical image classification and segmentation over traditional Unet (Ayadi et al., 2022).

In this paper, we propose a new architecture by implementing NST and an Xception-backed encoder-decoder network to train a model for salt segmentation. The synthetic training data is optimized by deep neural style transfer to mitigate domain discrepancy by learning features from field testing data but keeping the training label unchanged. Our tests show that introducing features from field testing data into synthetic training data will significantly mitigate domain discrepancy and provide better prediction results.

Methodology

In seismic acquisition, domain discrepancy could be introduced by data acquired at different survey areas with different signal-to-noise ratios and frequency bands. Various processing algorithms, e.g. migration with different levels of attenuation and anisotropy, will also bring shifts in the data domain for seismic interpretation. We are trying to leverage the ability of NST to mitigate this domain discrepancy. During the NST process, the neuron weights are not changed, instead, we modify the pixel value in each image to push the loss function between the content image and the style image to achieve a minimization by considering two loss functions: a content loss and a style loss. A content loss is calculated by Euclidean distance between the respective intermediate higher-level feature representation of the generated image ($\vec{x}$) and the input content image ($\vec{p}$) in layer l. A content loss can be defined as:

$$\mathcal{L}_{content}(\vec{x}, \vec{p}, l) = \frac{1}{2}\sum_{i,j}(F_{ij}^{l}(\vec{x}) - P_{ij}^{l}(\vec{p}))^2$$

Where F^l and P^l are the feature representation of $\vec{x}$ and $\vec{p}$. A style loss is evaluated by Gram Matrix, which is used to interpret style information in an image as it shows the overall distribution of features in a given layer. It is measured as the amount of correlation presented between feature maps in a given layer, and can be defined as:

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{ij}^l(\vec{x}) - A_{ij}^l(\vec{a}))^2$$

$$\mathcal{L}_{style}(\vec{a}, \vec{x}) = \sum_{l=0}^{L} \omega_l E_l$$

Where G^l and A^l represents the style representations of the generated image $\vec{x}$ and the original style image $\vec{a}$ in layer l. N_l is the number of feature maps and M_l is the size of the flattened feature map in layer l. ω_l is the weight given to the style loss of the layer l.

The total loss function is a sum of content loss and style loss:

$$\mathcal{L}_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{content}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{style}(\vec{a}, \vec{x})$$

Where α and β are weights for content and style respectively. They can be tweaked to alter the balance between training data and testing data. In this case, the content image is considered synthetic training data, and the style image is considered field testing data respectively.

We then consider NST results as the training data for an Xception-based encoder-decoder network. Compared with the original Inception network, Xception implemented depthwise separable convolution for image segmentation and classification with more efficiency in terms of computation training time. Figure 1 illustrates the overall architecture of neural style transfer and Xception network for seismic salt segmentation.

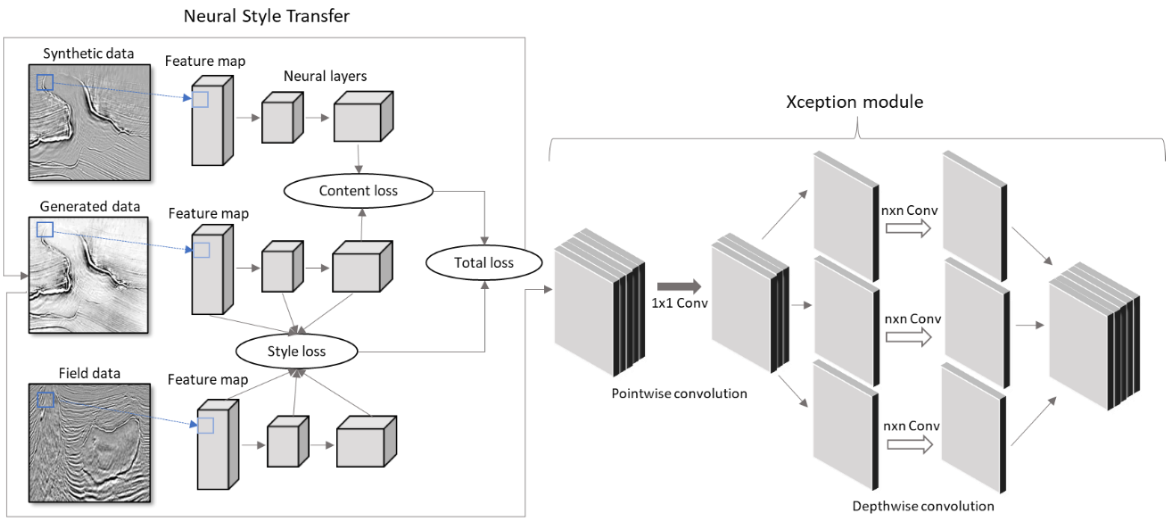


Figure 1: The overall architecture of neural style transfer and Xception module used for salt segmentation.

Examples

We used the synthetic SEG Advanced Modeling (SEAM) dataset as the synthetic training data, and the field data from the Gulf of Mexico as the testing data to validate the proposed approach. We consider the synthetic SEAM data as a content image, and the field data as a style image, to reconstruct synthetic data from testing data to generate neural transferred (NT) data. The newly created NT training data contains the original salt structure with specific features extracted from field data. The training labels are still unchanged. The NT training data and labels are then fed into the proposed Xception-based network to learn the mapping between the data and labels. At the inference stage, we implement NST again to consider the field testing data as a content image and synthetic training data as a style image to transfer features from the synthetic training data to the field testing data. The cross-feature referencing setup shows a better prediction result.

Figure 2 shows a comparison between the original synthetic data and the field testing data before and after NST. Figure 2c is created by transferring features from Figure 2b to Figure 2a and is used as training data to train the ML model. Figure 2d is created by transferring features from Figure 2a to Figure 2b and is used as the testing data to segment salt. The only label information we have is the synthetic label corresponding to Figure 2a. Figure 3 shows comparisons of salt prediction between different training and testing strategies. Due to the strong discrepancy between the synthetic training data and the field testing data, the traditional training & testing strategy does not work at all (Figure 3a). The NT training data could help to improve model training and shows slightly better result (Figure 3b). To train a model with cross-referencing features between synthetic training data and field testing data, the prediction result (Figure 3c) shows a significant improvement over traditional workflow.

Figure 4 shows the result of the Principle Component Analysis (PCA) on the latent-space representation of the NT synthetic training data, the original field testing data, and the NT field testing data. We project three types of data into the latent space by encoding layers of the Xception-based network resulting in latent vectors in a lower dimension, then implement PCA to reduce the dimensionality of latent vectors to increase interpretability as well as minimize information loss. Figure 4 indicates that the NT field testing data (Figure 4c)) presents a more similar feature representation as the training data (Figure 4a)), therefore the domain discrepancy is significantly reduced and results in better prediction.

Conclusions

In this paper, we propose a workflow to leverage NST and Xception-based modules to mitigate domain discrepancy in salt segmentation. NST helps to combine features between training data and testing data to reduce domain discrepancy and improve prediction accuracy. The PCA of latent-space representation shows that the NT testing data have more similar features to the training data, which validates the ability of NST in salt segmentation. The overall workflow could be implemented in different supervised deep-learning seismic interpretation workflows to provide a more generalized model.

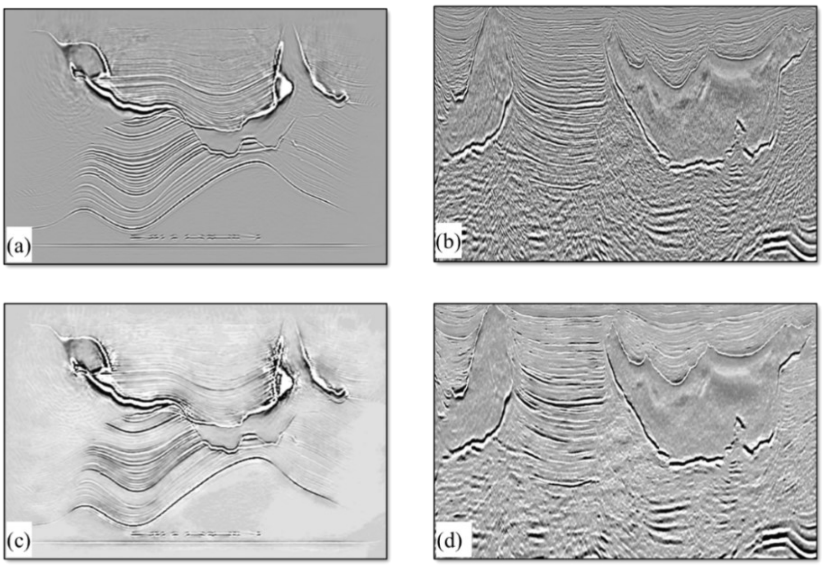
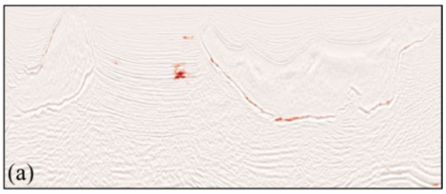
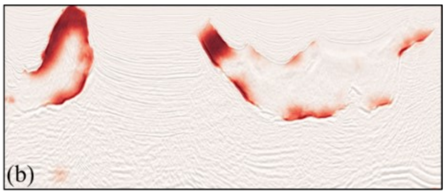
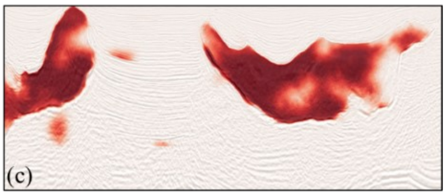


Figure 2: (a) The original synthetic training data; (b) the original testing field data; (c) The NT training data by transferring features from (b) to (a); (d) The NT field data by transferring features from (a) to (b). Notice (c) is considered as the training data to train a salt segmentation model and (d) is considered as the testing data.

Train & Test Strategy	Prediction Results
Train: the original synthetic data Test: the original field data	
Train: the neural transferred synthetic data Test: the original field data	
Train: the neural transferred synthetic data Test: the neural transferred field data	

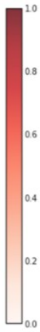


Figure 3: The comparisons of salt prediction between different train and test strategies.

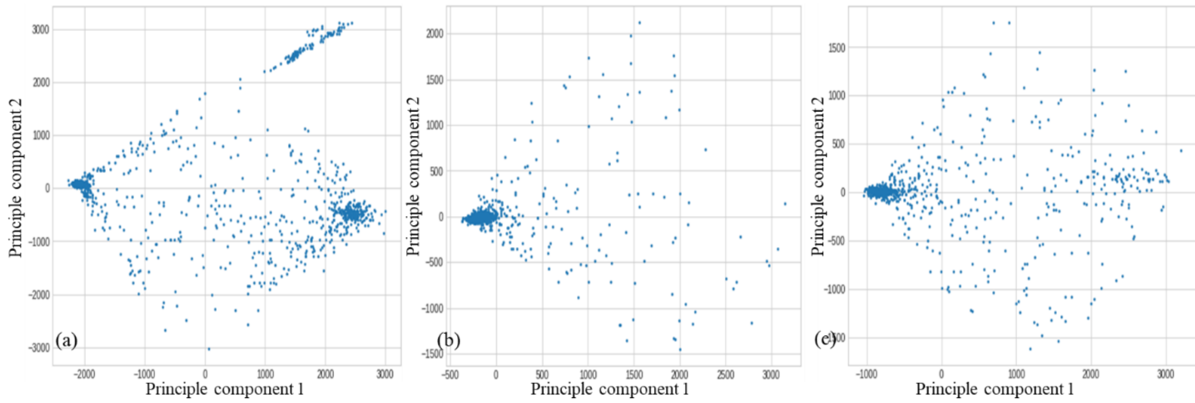


Figure 4: The PCA of latent-space representation from (a) the NT synthetic training data, (b) the original field testing data, and (c) the NT field testing data.

Acknowledgments

We would like to thank SEG and TGS to provide permission to use datasets in this study.

References

Ayadi, M., Ksibi, A., Al-Rasheed, A., and Soufiene, B., [2022] Covid-AleXception: a deep learning model based on a deep feature concatenation approach for the detection of Covid-19 from a chest X-ray image, *Healthcare,* **10**, 2072.

Chollet, F., [2016] Xception: deep learning with depthwise separable convolutions, arXiv:1610.02357v3.

Gatys, L., Ecker, A.. and Bethge, M., [2015] A Neural Algorithm of Artistic Style, arXiv:1508.06576

Ovcharenko, O., Kazei, V., Peter, D., and Alkhalifah, T., [2019] Style transfer for generation of realistically textured subsurface models, SEG Expanded Abstracts, 2393-2397.

Park, M.J., Jennings, J., Clapp, B., and Biondi, B., [2022] Realistic synthetic data generation using neural style transfer: application to automatic fault interpretation, SEG Expanded Abstracts, 1714-1718.