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Saliency-Map Guided Salt Prediction by a Multi-Channel Convolutional Neural Network

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Abstract

One of the major challenges in seismic imaging is accurately delineating subsurface salt. Since a salt boundary has strong impedance compared with other sediments, we build a saliency map with intensity and orientation to create a pixel-level model for salt interpretation. In this abstract, we train a saliency-map as an additional attribute to combine with the original seismic to predict salt bodies. We also train a saliency-map to classify multiple geological facies in a multi-channel convolutional neural network with residual net architecture to help build subsurface velocity models. Two examples are shown which demonstrate that a saliency-map-plus-seismic model successfully improves the accuracy of salt prediction and reduces artifacts.

Summary

Deep learning approaches have recently shown success in automating feature extraction from seismic data. These workflows significantly reduce the time required for the interpretation life-cycle. In this paper, we implement saliency maps as an additional seismic attribute to combine with the original seismic to predict salt bodies as a binary classification, then we apply saliency maps to classify multiple geological facies to help build subsurface velocity models. Two examples are shown which demonstrate that a seismic-plus-saliency-map model successfully improves the continuity of salt prediction and reduces unwanted artifacts. Different types of neural networks are also discussed which improve the prediction accuracy.

Introduction

One of the major challenges in seismic imaging is to accurately delineate subsurface salt. Imaging these features is important since many salt structures can form parts of a hydrocarbon trap. Inaccurate salt body interpretation can lead to failure in fully understanding a reservoir structure. Current seismic interpretation methods require experienced interpreters to manually label the boundary of salt features, which is a very time-consuming and labor-intensive process. A subjective human bias can also exist and lead to erroneous interpretation results.

In recent years, computer-aided automatic or semi-automatic seismic interpretation tools have been implemented to assist and speed up the interpretation process (Jing et al., 2007, Amin and Deriche, 2015).

Those deterministic algorithms help improve the accuracy of salt body detection, especially the bottom of salt. As geophysical features from a dataset get more complex, using individual seismic traces may not be an efficient way to analyze seismic data and segment specific features. The advent of machine learning algorithms brought substantial learnings from the computer vision and medical industry and shown success in automating and accelerating the identification of structures in seismic data. Different technologies, such as k-means clustering (Di et al., 2018), extremely randomized trees classification (Guillen et al., 2015), and deep neural networks (Shi et al., 2019), have been implemented to identify structures in seismic data via unsupervised and supervised learning.

From this research, convolutional neural networks (CNNs) have proven to be an effective approach to classify seismic features to help in geophysical interpretation. CNNs are considered as end-to-end, pixels-to-pixels networks which leverage the semantic information contained in a series of convolutional layers and assign the densely semantic meaning back to the pixels that generate the semantic information. Di et al (2018) performed an investigation of why CNNs perform better than other machine learning approaches. They claim that the CNN can automatically generate a suite of features then optimize them during the training process, meanwhile, the patch-based segmentation incorporates the local seismic reflection patterns into building the mapping relationship between the seismic signals and the target structures. Ye et al. (2019) discussed using a smoothed P-wave migration velocity as a second input channel, along with an RTM image for training the network. The result showed the artifacts are reduced significantly. Then a second workflow was implemented to mitigate oscillations and further improved prediction results.

Seismic attributes are frequently used to help classify geological features in seismic data. A seismic attribute is a quantity extracted from seismic amplitude data that can be studied to enhance subtle geological features where amplitde data alone can not identify. Therefore seismic attributes could be used to quantitatively measure a seismic characteristic of interest. Guillen et al. (2015) applied the second derivative and curve length calculated from seismic data to assist the ensemble approach for salt body detection. Several ensemble algorithms, such as Gradient Boosting Trees, Extremely Randomized Trees, and Random Forests, were top-performing learning algorithms among others, and achieve high accuracy. Shafiq et al. (2015) proposed a novel seismic attribute, the gradient of textures, to quantify texture variations in 3D and detect salt using the changing gradient of texture along their boundaries. Besides the novel attribute, they implemented region growing and morphological operations to remove noisy boundaries and detect the boundary surface of the salt body effectively. Shafiq et al. (2016) described a saliency-based attribute to detect salt bodies in a seismic volume. Their attribute is based on the saliency theory and modeling of the human vision system, by combing spectral decomposition and center-surround windows to generate a visual saliency-based attribute. Jiang et al. (2020) analyzed different seismic attributes, by different machine learning ensemble classifiers, to construct a ranking system of the importance index. They picked several of the most important attributes toward the predictability of salt bodies, such as response frequency, relative amplitude changes, or apparent polarity, and used them as additional input channels to feed into a multi-channel convolutional neural network to detect salt bodies. This achieved higher accuracy than the seismic-only model.

In this study, we implement a multi-channel CNN architecture by combining saliency maps and the original seismic amplitude data as input channels to perform salt prediction. Tests with binary classification and multi-label classification show great improvement in the accuracy of salt body prediction. Compared with other attribute-based machine learning approaches (Guillen et al., 2015; Jiang et al., 2020), this saliency map approach brings superior prediction accuracy with less memory requirements.

Method

Saliency maps were first introduced by Itti et al. (1998) for feature extraction in neuroscience images. They represent the conspicuity, or saliency, at every location in a visual field using a scalar quantity to guide the selection of attended locations, based on the spatial distribution of saliency. In computer vision, saliency maps process images (Perazzi, et al., 2012) to differentiate visual features, e.g. colored images are converted to black-and-white images to analyze the strongest colors present in them (Figure 1).

Figure 1—An example of images and their saliency maps. (a) Colored images; (b) Their saliency maps. (Modified from Perazzi, et al, 2012

To build a proper saliency map by seismic data, colors, intensity, and orientation are considered to create a pixel-level model for feature extraction in seismic amplitude images. Shafiq et al. (2017) developed a novel workflow for saliency detection. They decomposed a 3D FFT spectrum from the seismic data in conjunction with a directional center-surround (DCS) model and a top-down approach to depict variations in motion along inline, crossline, and depth (or time) in 3D data. In their workflow, 3D FFT with a sliding window was used to calculate the spectral cube, then performed a spectral decomposition to obtain the spectral along different directional planes. Following another step to calculate spectral energies for each cube, we can stack all directional cubes together with specific weighting coefficients based on the features we want to highlight. We adapted their algorithm with a variable Gaussian weighting coefficient along different directions to fine-tune the saliency detection and generate a saliency map for a subset of the SEG Advanced Modeling (SEAM) seismic dataset (Figure 2). A Hanning filter was implemented to smoothly filter some edge effects after 3D FFT calculation.

$$S[x, y, z] = a * S_x[x, y, z] + b * S_y[x, y, z] + c * S_z[x, y, z]$$

Where $\boldsymbol{a}$, $\boldsymbol{b}$, $\boldsymbol{c}$ are variable directional weighting coefficients. $\boldsymbol{S_x}$, S_y, and $\boldsymbol{S_z}$ are directional saliency map along inline, crossline, and depth direction:

$$S_m[x, y, z] = \frac{\partial w_c^T I + b_c}{\partial I}$$

Where $\boldsymbol{I}$ corresponds to the spectral cube, $\boldsymbol{c}$ is the feature class, $\boldsymbol{w}$ and $\boldsymbol{b}$ represent the weighting coefficient and bias for the feature class we want to highlight. $\boldsymbol{m}$ corresponds to inline, crossline, or depth direction.

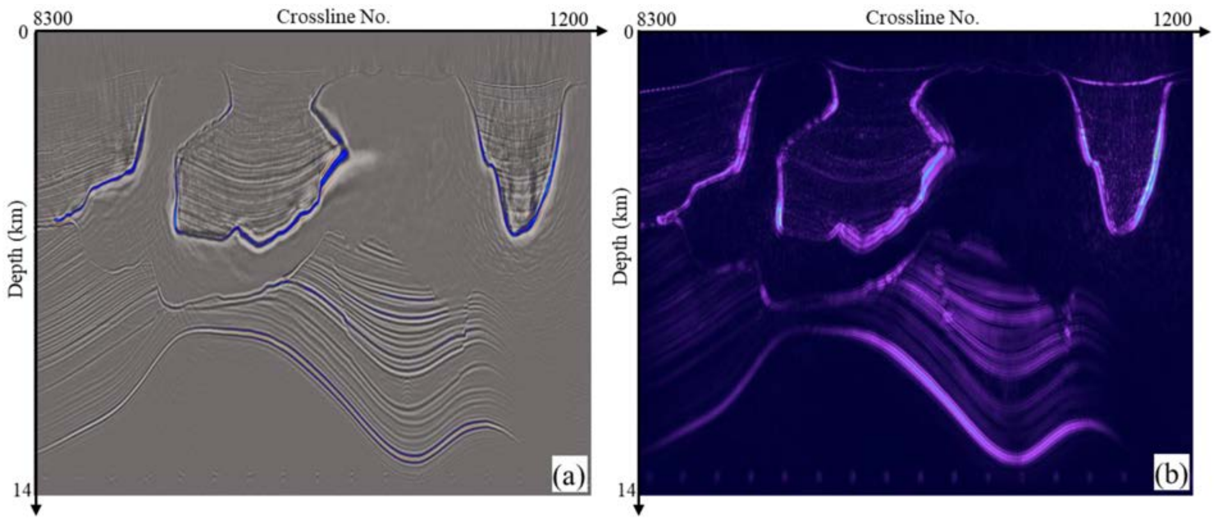

Figure 2—(a) Original seismic data and (b) its saliency map.

We then considered the saliency map, as an additional input training data, along with the original seismic data, as dual-channel data to feed into a multi-channel CNN to train the model. Conventional CNN architecture only takes seismic data as training data to train the model and perform image segmentation, it helps to extract the most apparent features in seismic data and it can distinguish between different objects.

However, some subtle differences between objects could be ignored and misclassified in a complex area. Providing additional information on the predictability of our target is necessary. Data augmentation is one of the popular ways to artificially expand the size of a training dataset by creating modified versions of images in the datasets. However, augmented datasets still have the same similar feature properties as the original dataset, therefore the trained model may predict false-positive masks and misclassified images. In contrast, seismic attribute, such as a saliency map, depicts the most important features from an object, and we can manually fine-tune the parameters, such as the length of Fourier Transform window or Gaussian weighting coefficients, to enhance specific targets, such as a salt boundary. It provides additional information to assist the neural network to encode what the specific object is, capture the context in the seismic data, and enabling precise localization using transposed convolutions to determine where those features belong to and maximize visualization of the class of interest.

Figure 3 shows a workflow that combines a saliency map with seismic data for a multi-channel CNN. The input layer is the two-channel data and output could be either binary or multi-label based on our training datasets. During the training process, a saliency map will be divided into a group of sub-cubes and provide an additional feature map to augment the feature map generated from the seismic data, then the enhanced feature maps are used to encode the next level of feature layers. In Figure 3, each block was processed separately by a group of a convolutional layer, batch normalization layer, and an activation layer, or by a max-pooling and dropout layer. The images shown in each block were explicit feature maps extracted from the different depths in the deep neural network. At different depths, a convolutional layer will generate various feature maps and we only pick one of them to be included in Figure 3. The last dense layer and activation function are used to Categorically classify the different class numbers we assigned when training the model.

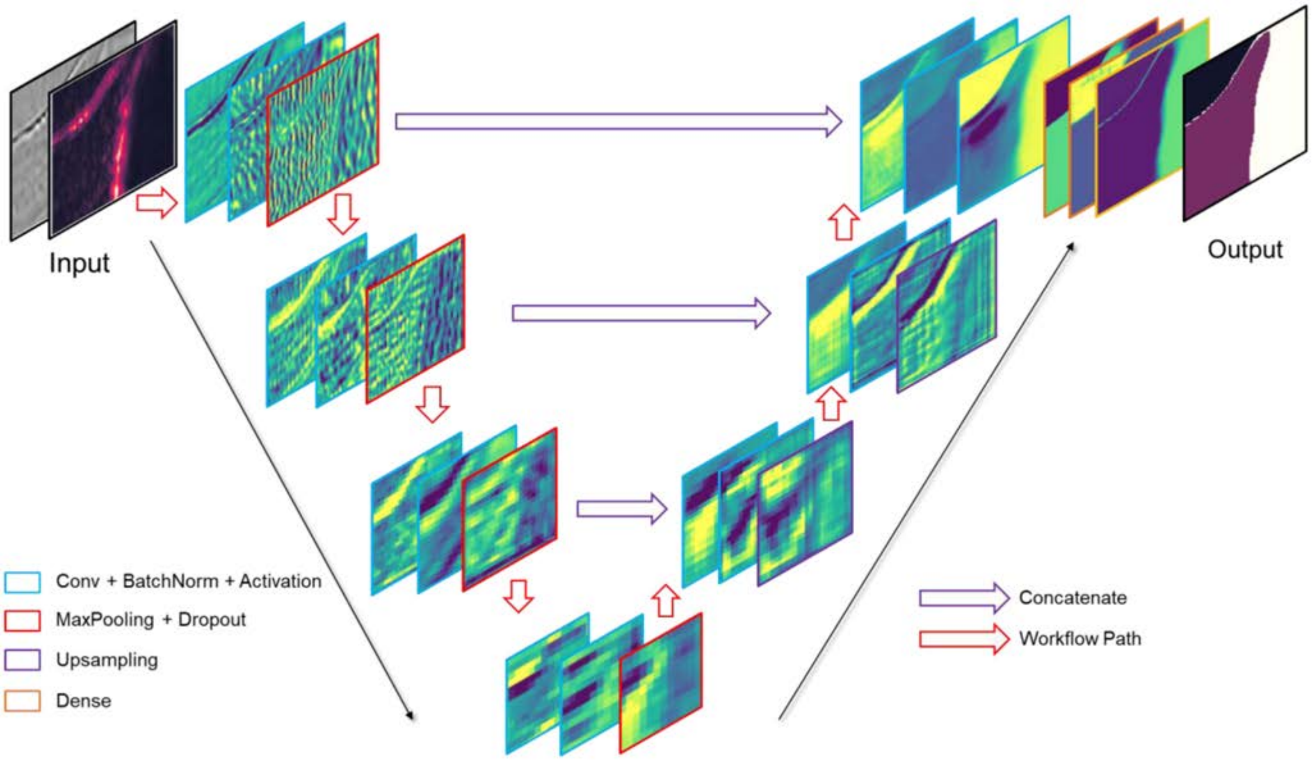

Figure 3—The deep convolutional network with saliency map. The inputs are seismic and saliency maps, the output is classified segments. Each layer shows different feature maps at different depths of the neural network.

In our tests, two different models were trained: a binary model, which classifies salt and no-salt objects, and a multi-label model, which identifies water, sediments, shallow & deep salt, and basement. For different models, we use different metrics to evaluate the accuracy. For binary classification, we use the well-known metrics of Interaction over Union (IoU) to evaluate the accuracy:

For multi-label classification, we implement the categorical loss function to check if the index of the maximal true value is equal to the index of the maximal predictive value, then calculate the mean accuracy across all predictions. The categorical cross-entropy is represented as:

$$-\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C}\alpha_{y_i \in C_c} log\, p_{model}[y_i \in C_c]$$

Where the double summation is over the observations i, whose *number is* N, and the categories c, whose number is C. The term $\alpha_{y_i \in C_c}$ is the indicator function of the ith observation belonging to the cth category. The term $\boldsymbol{p_{model}}[\boldsymbol{y_i} \in \boldsymbol{C_c}]$ is the probability predicted by the model for the ith observation to belong to the cth category. In our case, if you have more than two categories, the neural network outputs a vector of C probability, each giving the probability that the network input should be classified as belonging to the respective category.

Figure 3 shows feature map visualization between a seismic-only model and a seismic-plus-saliency-map model during different convolutional layers. A feature map is a function to map a data vector to feature space. Each convolutional layer will try to map the input features to hidden units to form new features to feed to the next layer. Feature visualization translates the internal features present in an image into visually perceptible or recognizable image patterns. Therefore feature map with more visible information will help to detector more weak features from input data.

Examples

In our tests, we used the synthetic SEG Advanced Modeling (SEAM) data to train our models and compare them with a traditional deep learning model. The SEAM data represents the deepwater regions of the Gulf of Mexico and contains sediments with similar amplitude values to the salt body, which bring additional challenges to the interpretation process. In each test, we fixed the batch size, the number of epochs, and the number of convolutional layers to be consistent across the different approaches during the training process. We randomly picked a 5% subset of the data for training and predicted the other 95%. Figure 4 compares the prediction results between different approaches. Figure 4(a) represents the original seismic data. Figure 4(b) is the prediction result generated by a seismic-only model. In this case, we only used seismic data as an input channel to train the model and predict the rest. Some artifacts are seen within the salt body as it was classified as non-salt. Figure 4(c) shows the prediction result by our approach, the seismic-plus-saliency-map model, the IOU accuracy is improved from 88.5% to 91.1%. Some areas which were misclassified by the seismic-only model are corrected. Since we considered the saliency-map attribute as an additional input data, the memory requirement of this approach requires two times greater than the seismic-only model. This could be leveraged once we deploy the model into the cloud-based architecture.

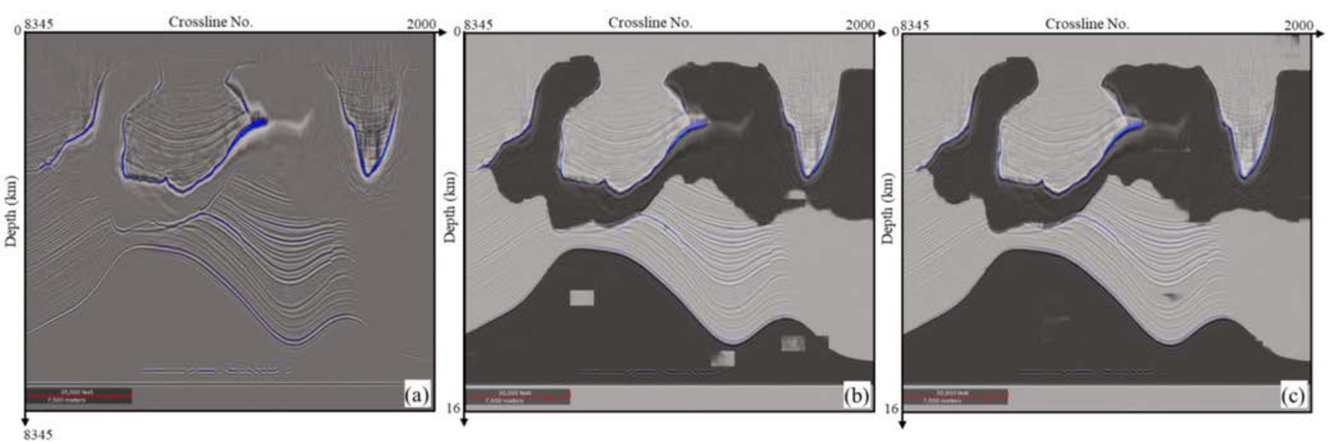

Figure 4—The results of binary salt classification. (a) The original seismic; (b) Prediction by seismic-only model; (c) Prediciton by seismic-plus-saliency-map model. Notice that some areas misclassified in deep salt are corrected in (c).

Figure 5 shows the multi-label classification results. We manually divided the training dataset into five classes: water, shallow and deep salt, sediments, and basement. The difficulty in this model is that there are several small salt blocks with weak boundaries which make classification difficult. It is also difficult to differentiate shallow and deep salt when only using seismic amplitude data (Figure 5b). There are also several small misclassified areas along the boundary of the shallow salt body. Figure 5(c) is a classification result using the seismic-plus-saliency-map model. The shallow salt body is classified well with fewer artifacts, and the areas around the shallow salt boundary are correctly identified. The categorical accuracy of the seismic-plus-saliency-map model is improved from 90.1% to 94.6%. The memory requirement is again two times larger than using a seismic-only model since both the training and the prediction process require seismic attributes the same size as original seismic data. We observed the seismic-plus-saliency-map model could obtaining higher accuracy, especially at the boundary, mainly because the saliency map significantly highlighted the boundary as a pre-processing feature. We noticed that some artifacts were generated in the deep salt body. They can be removed by postprocessing methods such as contouring or median filters.

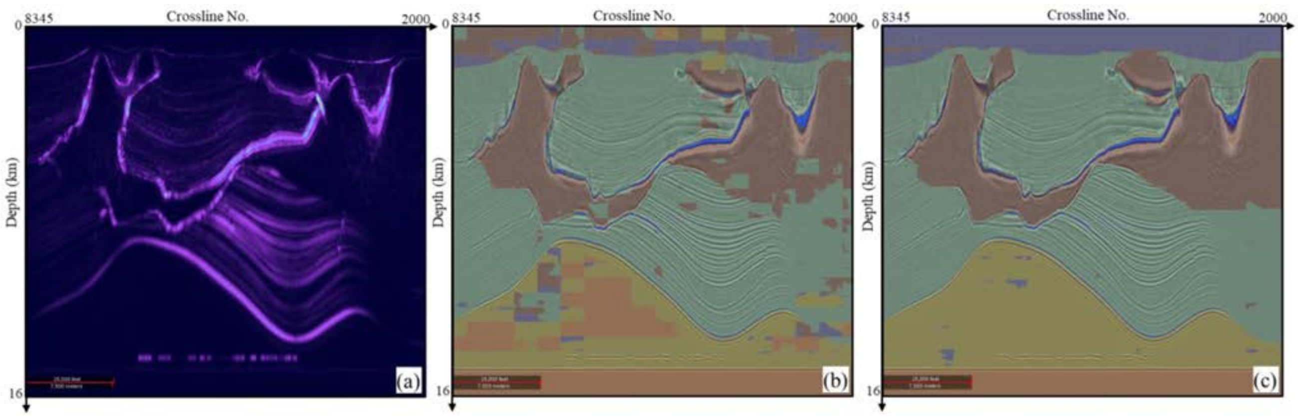

Figure 5—The results of multi-label classification. (a) The saliency map; (b) Prediction by seismic-only model; (c) Prediction by seismic-plus-saliency-map model.

Figure 6 shows a comparison chart of loss and accuracy during training between a seismic-only model and a seismic-plus-saliency-map model. Figures 6(a) and (b) present the training loss and accuracy when train a seismic-only model. The training loss is gradually decreased while training accuracy increases with epochs. However, the validation loss and accuracy show significant volatility which could result in the model overfitting. On other hand, Figures 6(c) and (d) represent the training loss and accuracy by the seismic-plus-saliency-map model. It shows a much less volatility effect compared with that from the seismic-only model. The seismic-plus-saliency-map model also shows faster convergence than the seismic-only model which indicates that fewer epochs are required to achieve high accuracy.

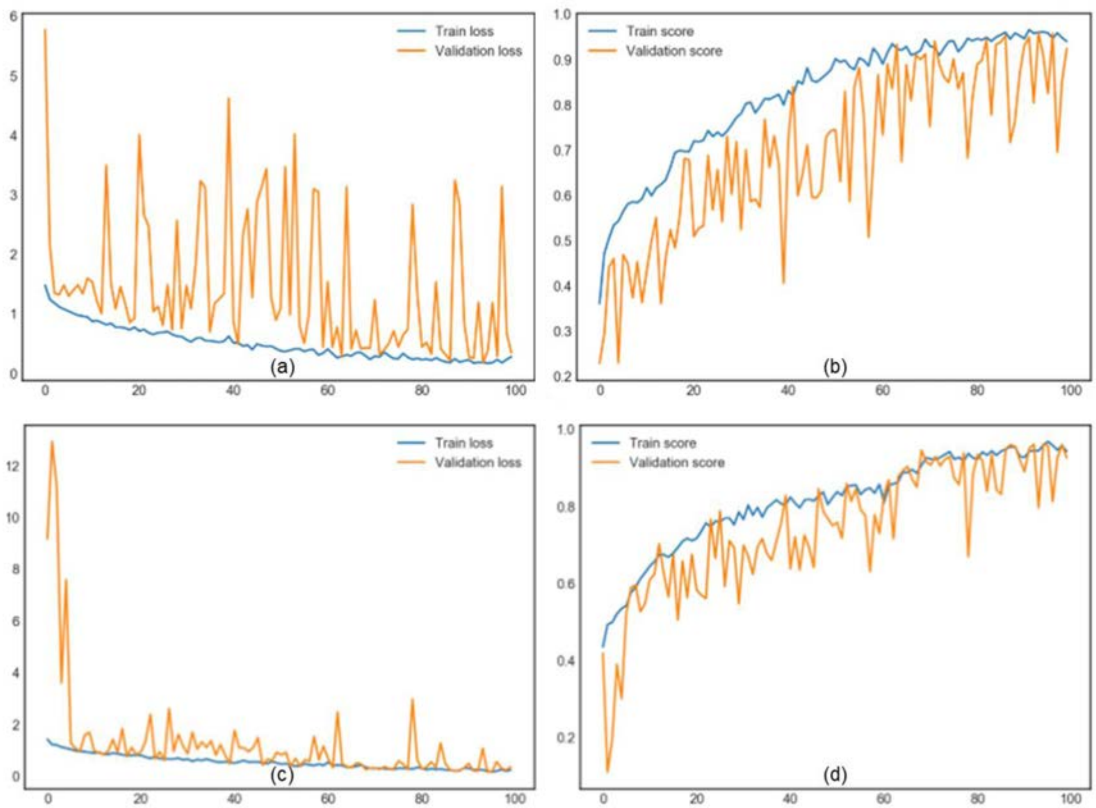

Figure 6—A evaluation matrix comparison of multi-label prediction during a training workflow between the seismic-only model and the seismic-plus-saliency-map model. (a) Training loss by the seismic-only model; (b) Training accuracy by the seismic-only model; (c) Training loss by the seismic-plus-saliency-map model; (d) Training accuracy by the seismic-plus-saliency-map model. The horizontal axis is the number of the epoch, the vertical axis is the training loss or accuracy degree respectively.

Discussion

Research interest in neural networks for the hydrocarbon industry to solve geophysical interpretation issues is high because of the effectiveness of the training and prediction process. Different combinations of neural networks have also been shown to be very effective for solving different challenges. During our tests, we implemented a classical U-Net architecture (Ronneberger et al., 2015) with a modified residual network (which will be submitted as a companion paper). The residual unit helps when training deep architecture and features accumulated in residual layers ensure better feature representation for segmentation tasks. Besides the classical U-Net architecture, other modified U-Net architectures show good performance on image segmentation and pattern recognition, such as Attention U-Net (Oktay et al., 2018), which applies an attention gate model to automatically learn to focus on target structures of varying shapes and sizes. MultiRes U-Net (Ibtehaz and Rahman, 2020) was introduced to replace the sequence of two convolutional layers with the multi residual blocks to formulate a compact analogous structure with less memory. These different versions of U-Net will be tested and optimized for geophysics and could bring additional benefits to help various seismic interpretation tasks, such as fault prediction or multi-facies classification. Additional tests using real data will be presented in future publications.

Jiang et al. (2012) discussed the implementation of multiple attributes, e.g. the combination of response amplitude, response frequency, relative amplitude change, and apparent polarity, to help the segmentation of seismic data in a CNN architecture. It shows good accuracy but could require large memory allocation since each attribute has the same memory requirement as the original seismic amplitude data. Our approach in this paper chooses only one attribute which could best describe the seismic salt feature, and achieve high accuracy. Further work could be completed to evaluate how other attributes take effect on the predictability of salt body or other geophysical features, such as the horizon, channel, or multi-facies interpretation.

Conclusions

In this paper, we present a novel approach to combine saliency maps as an additional channel to feed into a neural network to train a deep-learning model. The saliency map acts as a preprocessing step to delineate the most important features, e.g., the strong reflection at the salt boundary, in seismic data and provides additional information to the neural network to distinguish and locate specific features. We demonstrated that a saliency-map-assisted model could significantly improve the accuracy of salt prediction with fewer artifacts, especially at the salt boundary. Different neural network architectures were also discussed and could be implemented in future work.

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