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Deblending using convolutional neural networks

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Abstract

Machine learning has been a booming subject in computer science and its applications have been made in various subjects including geophysics. Convolutional Neural Networks (CNNs) have great potential for solving image processing problems like denoising and interpolation. Deblending, considered as an under-determined denoising problem, falls into this category. In this report, we use CNN to replace the deblending operator and its performance is analyzed. We use a 4-layer U-Net to perform deblending on synthetically blended shots from a wedge velocity model with point scatterers. We test out different hyper-parameters and the trained model could successfully remove the noise and preserve diffractions from the scatterers with some tolerance. The generality of the model is evaluated by testing the model on an easier 2-layer velocity model. The model can successfully identify and recover most part of the primaries but fails to deal with some interferences and leaves them muted.

Theory

The neural network architecture to solve the problem is the U-Net (Ronneberger et al., 2015). The U-Net was designed based on the CNNs and bridge connections were added so that it performs fast and well especially for solving segmentation problems.

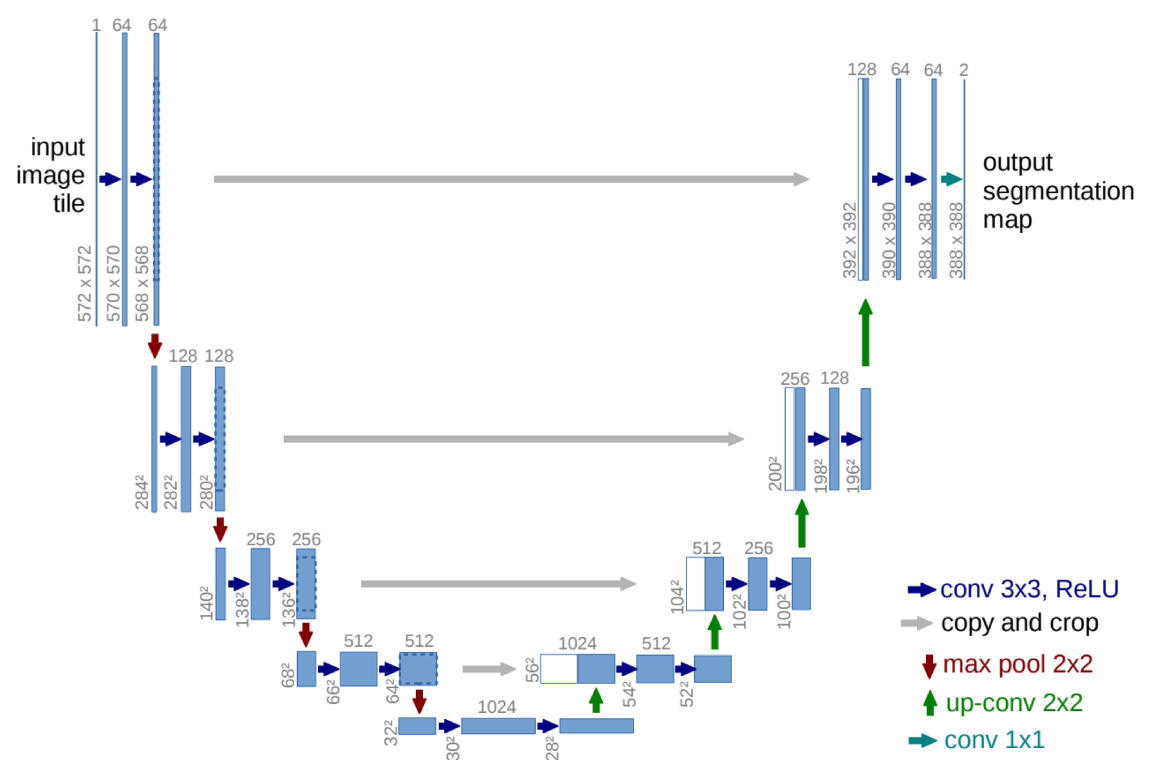

FIG. 1. Diagram of U-Net model modified from Ronneberger et al. (2015). The gray arrows refer to the bridge connections that directly pass the features from down-going layers to up-going layers.

We use L_2 square or MSE for the loss function, which is defined as

$$L = \text{mean}\left(\left\|Y - Y_{pred}\right\|_2^2\right) = \frac{1}{N_s}\sum\frac{1}{N_p}\sum\left(Y - Y_{pred}\right)^2$$

Synthetic Data Examples

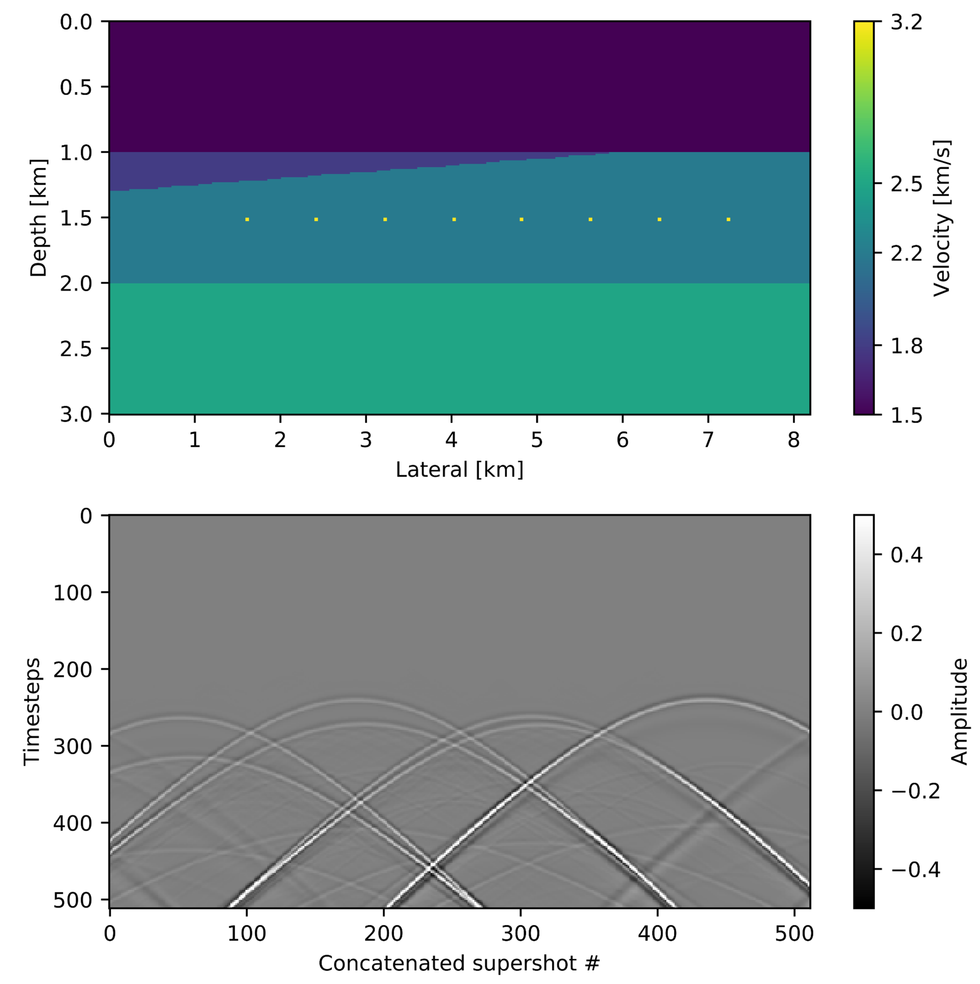

FIG. 2. The inputs fed to the U-Net model. The plots show the corresponding input (above) and label (bellow) pair at the 120th receiver, with 512 receiver slices in total.

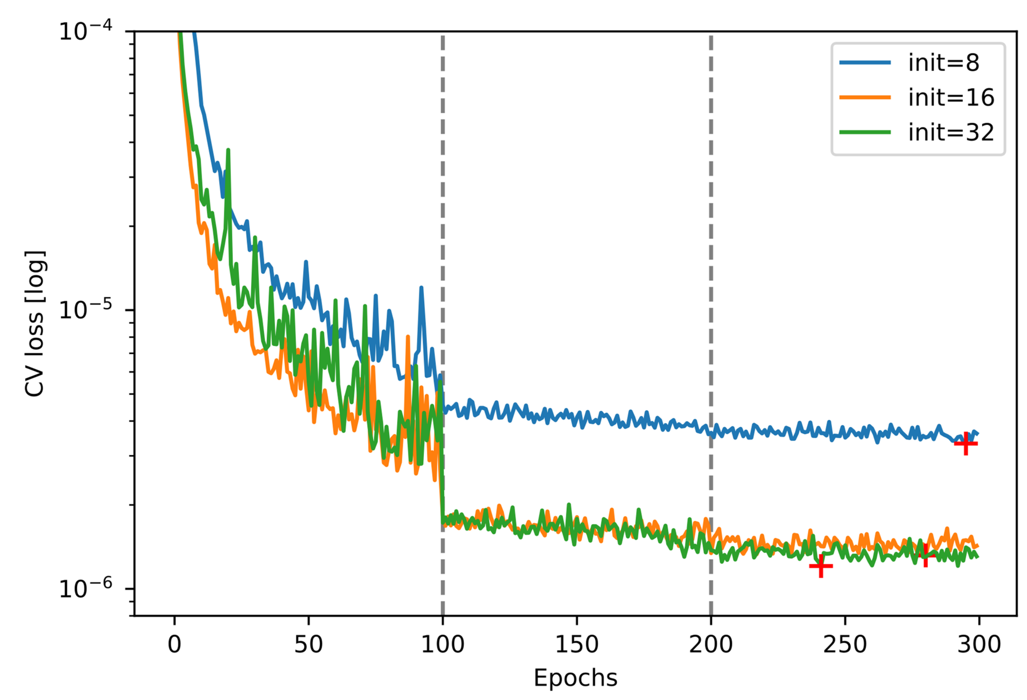

FIG. 3. The cross comparison of L_{val} with varying initial filters. The blue, orange and green lines refers to the cases with 8, 16 and 32 filters, respectively. Red crosses stand for the least L_{val} on each line.

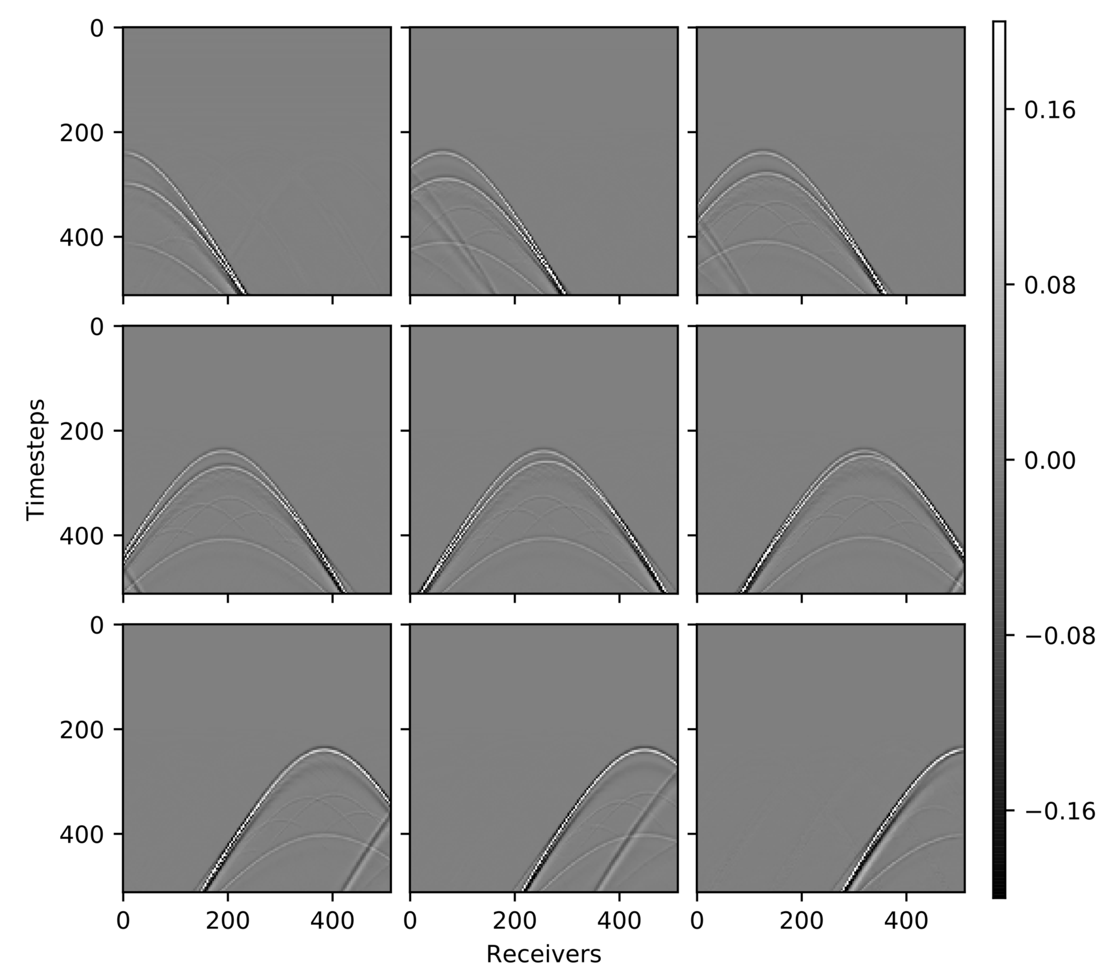

FIG. 4. The prediction on the whole dataset containing both the training and validation set (transposed to the shot domain). Note the preservations of the diffractions.

Synthetic Data Examples

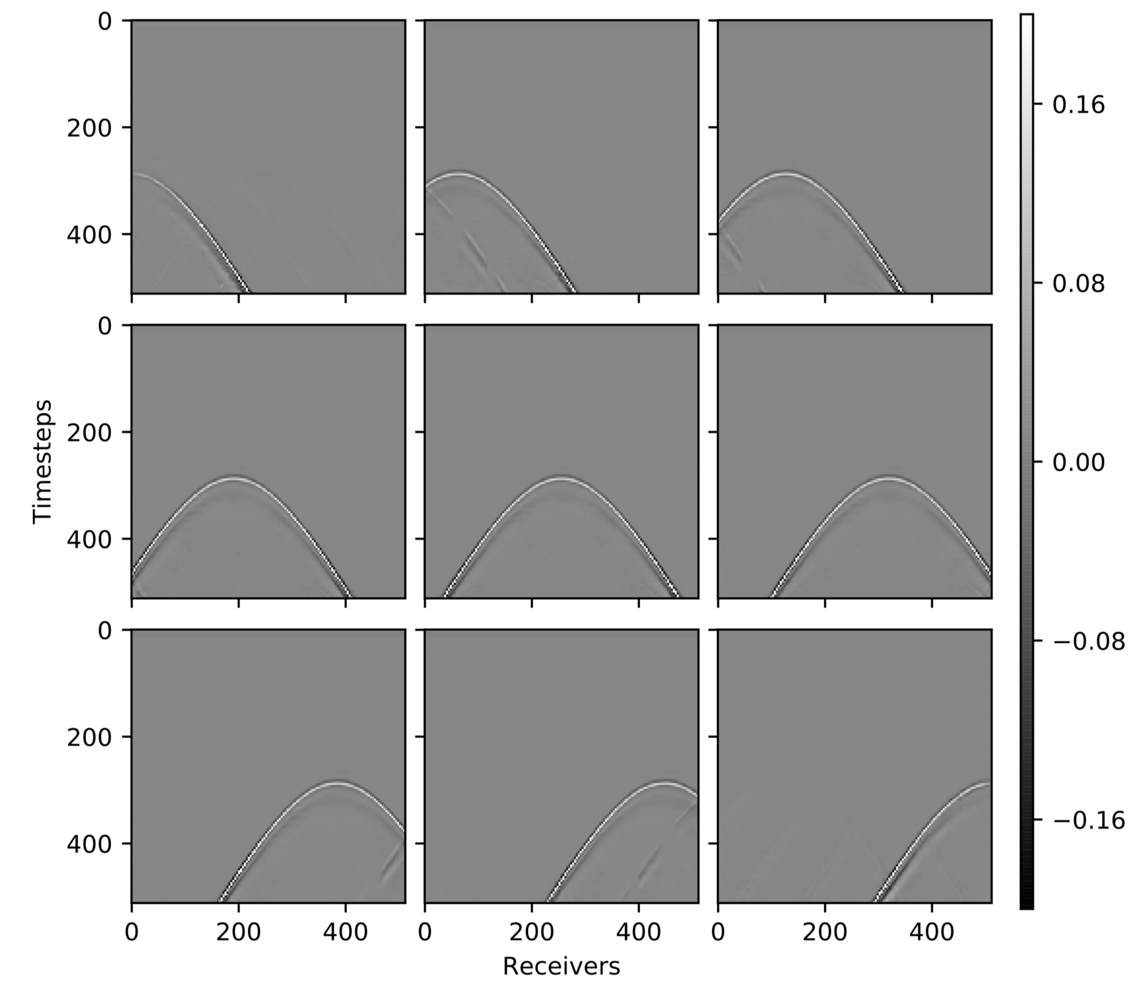

FIG. 5. Predictions for blended data from a two-layer model.

Conclusion

We trained a U-Net model to perform deblending. We tried several optimization and network parameters and found the best combination. In the case where the training and test data come from the same velocity model, the network performs well by preserving small diffractions and correctly identifying primaries. It performs a bit worse for the shots at the edge of the model because of the lack of training pictures representative of this case. For the case where the test data comes from a different model than the training data, the network performs okay but not as well as the first case. In this case, the test model was simpler than the training model, so the test is not conclusive and more work is required to fully understand how to generalize the network to new problems. To address these issues we plan to investigate in generalizing the model by gradient boosting, and provide several models for training.

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