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The Imaging of Sparse Seismic Data using Convolutional Neural Networks

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ABSTRACT

Convolutional neural networks (CNNs) are investigated for the imaging of sparse seismic data. Synthetic data are first generated from a suite of subsurface interface models, and a CNN with a U-net architecture is trained and implemented on a workstation with a NVIDIA RTX 2070 GPU. The U-net is an encoder-decoder neural network architecture consisting mainly of two paths, the contracting path (encoder) and expanding path (decoder). Each path consists of repeated applications of convolutions, concatenation, activation functions, max pooling and dropout operations which play the roles of capturing and reconstructing important features from the input images. From the trained CNN, very good imaging results are obtained even when the spatial sampling of the data is sparse. CNNs applied to seismic imaging therefore have the potential of obtaining improved seismic imaging results as compared to more traditional seismic imaging methods even when the spatial sampling of the data is sparse. The imaged models can also then be used to generate more densely sampled data and in this way be used to interpolate the seismic data to a finer spatial grid.

The Imaging of Sparse Seismic Data using Convolutional Neural Networks

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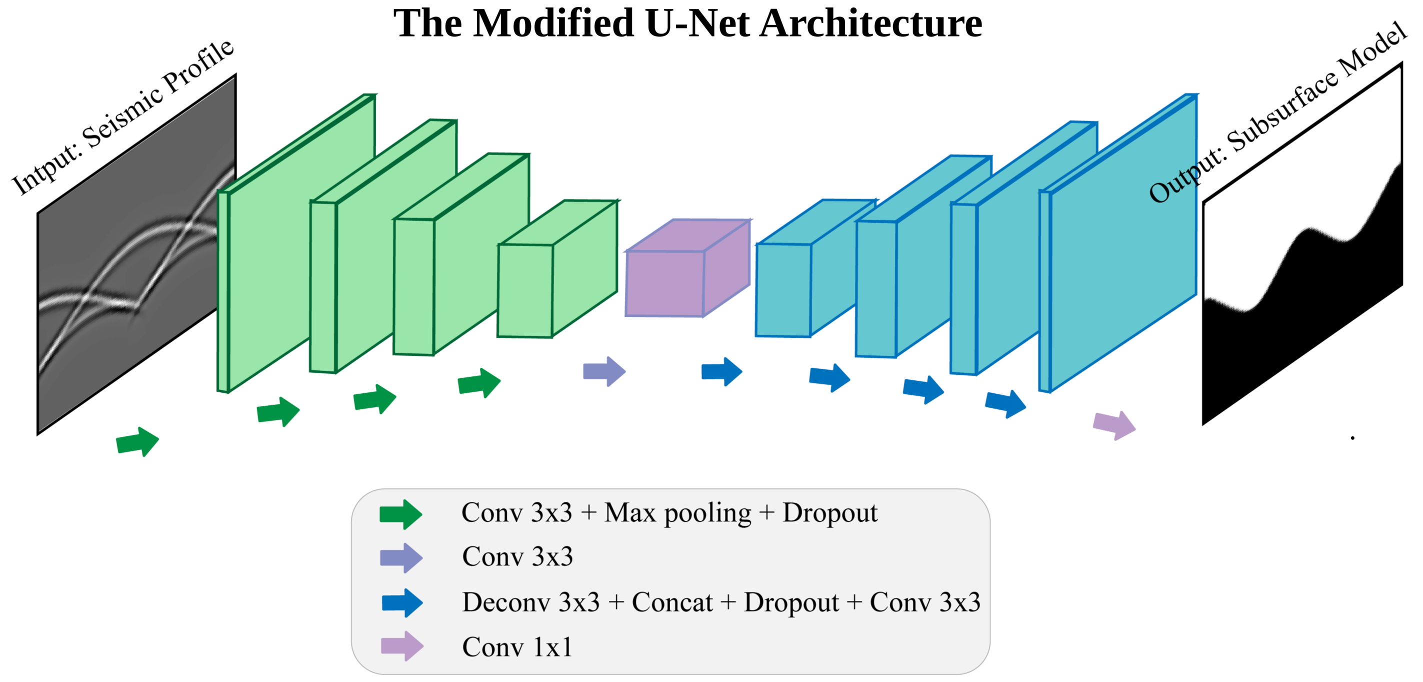
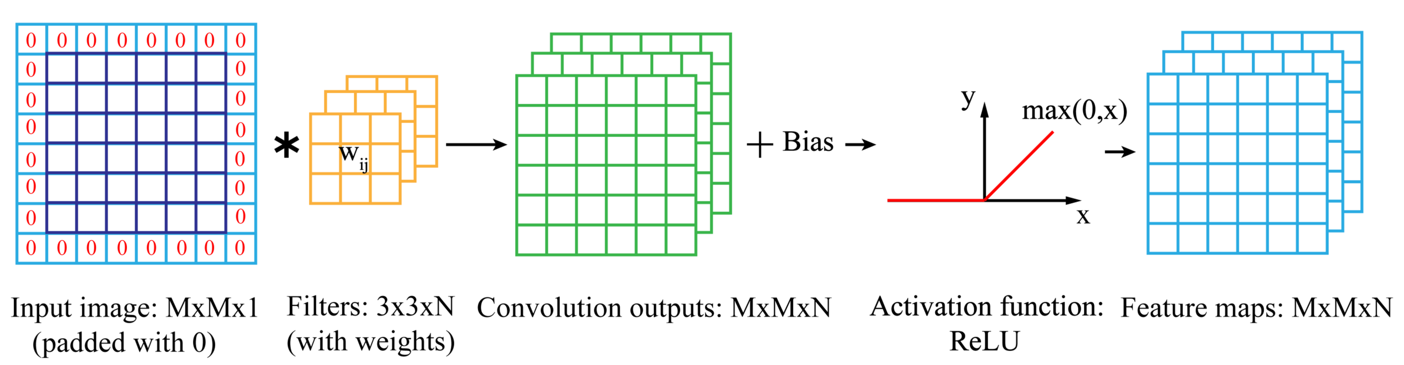
The Modified U-Net Architecture



This illustrates a simplified architecture of the modified U-Net Convolutional Neural network in this study. The U-net is an encoder-decoder neural network architecture consisting mainly of two paths, the contracting path (encoder) and expanding path (decoder).



This shows an example of a single convolutional layer with 3x3 kernels (filters).

Model Evaluation and Optimization

Loss Function

- Binary Cross entropy

$$L=\frac{1}{N}\sum_{i=1}^{N} y_i \log(p(y_i)) + (1-y_i)\log(1-p(y_i))$$

Metrics

- Binary Accuracy=(TP+TN)/(TP+TN+FP+FN)
- Dice Coefficient=2TP/(2TP+FP+FN)

Optimizer

Adaptive Moment Estimation (Adam)

The pixel values of upper layer and lower layer in the model are assigned 1 and 0, respectively.

The $p(y_i)$ is the probability distribution of the sigmoid function.

For all the pixels in the imaged model:

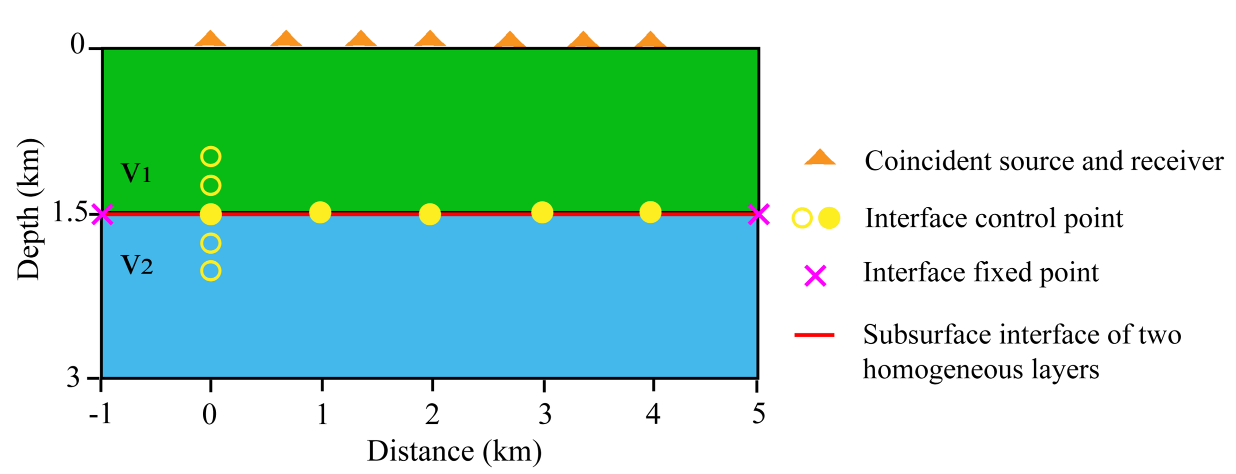
TP: Actual value is 1, predicted value is 1

TN: Actual value is 0, predicted value is 0

FP: Actual value is 0, predicted value is 1

FN: Actual value is 1, predicted value is 0

Synthetic Subsurface Interface Model and Zero-offset Seismic Data

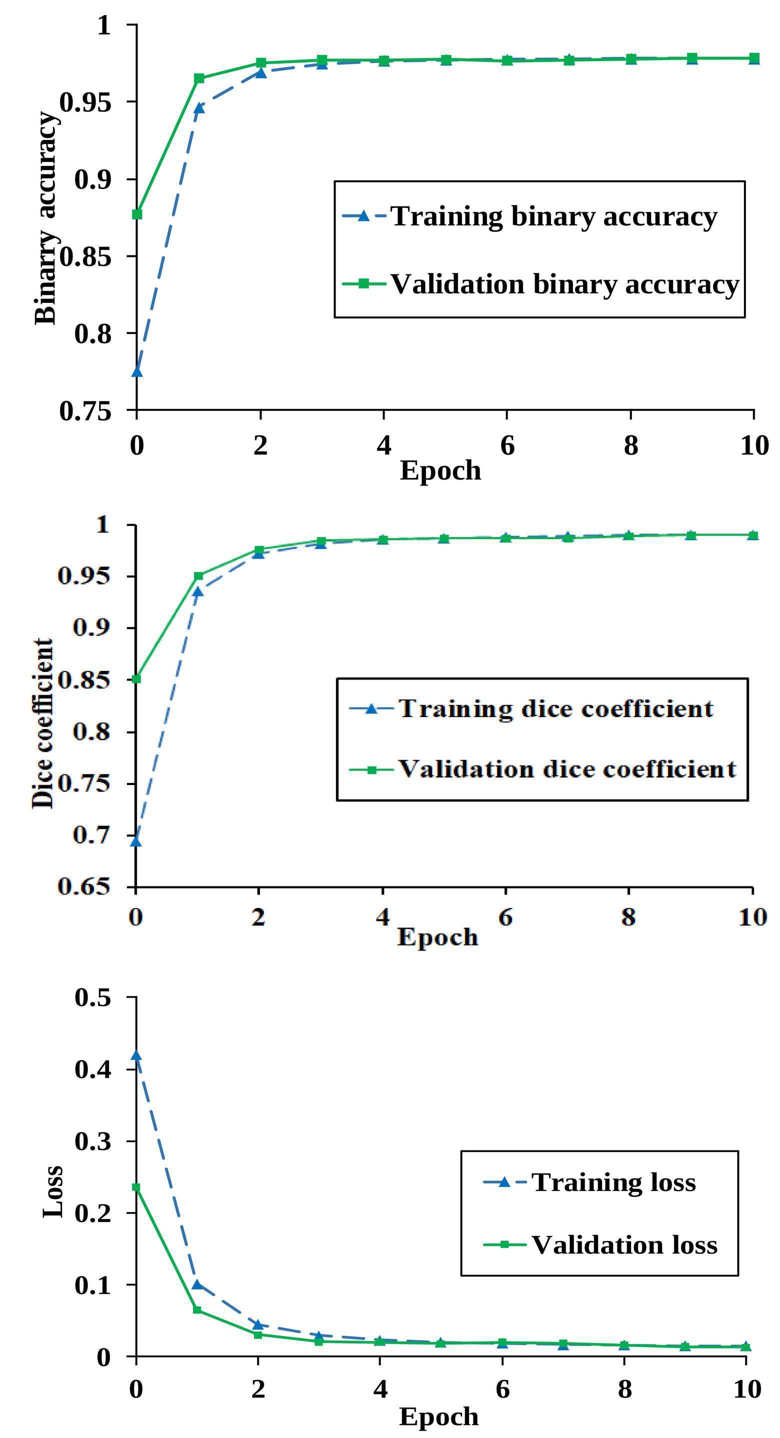


A diagram for the building of the subsurface interface models. There are 5^5 or 3125 interface models and 3125 corresponding computed seismic reflection profiles. The synthetic zero-offset seismic reflection data with 101 seismic traces are then generated using the Gaussian beam synthetic modeling.

Whole dataset (5^5=3125) → Randomly divided

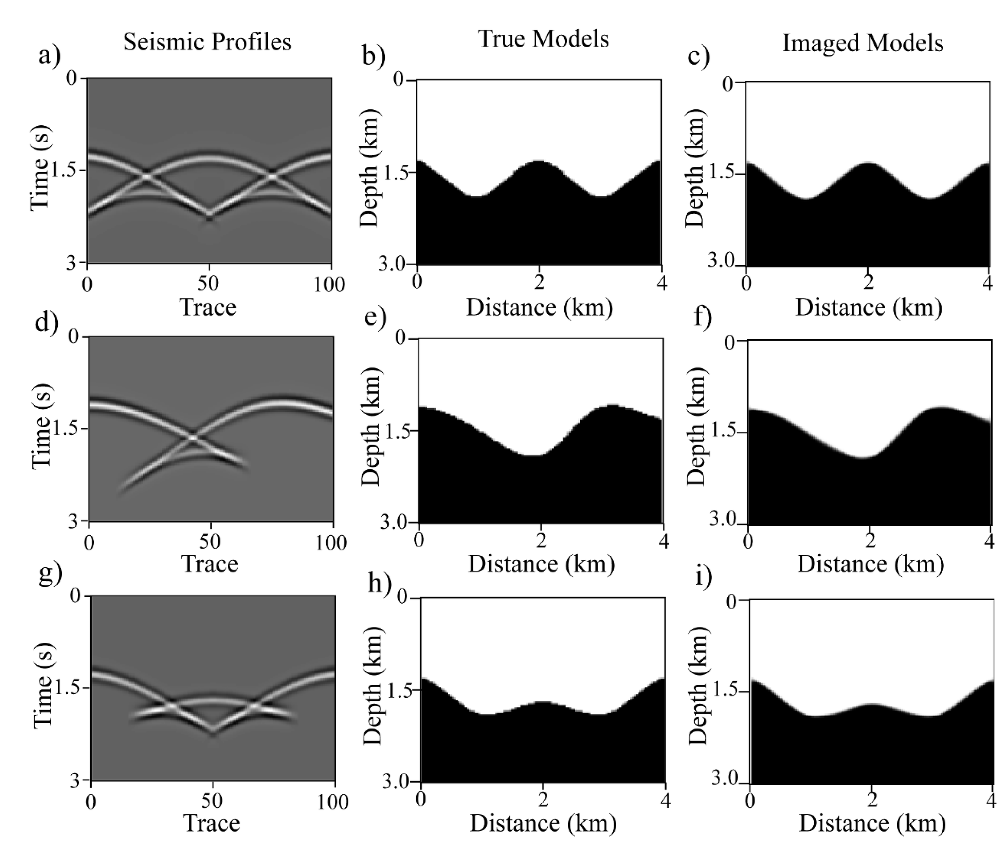
- Training dataset (60%):1875
- Validation dataset (20%):625
- Test dataset (20%):625

Model Training



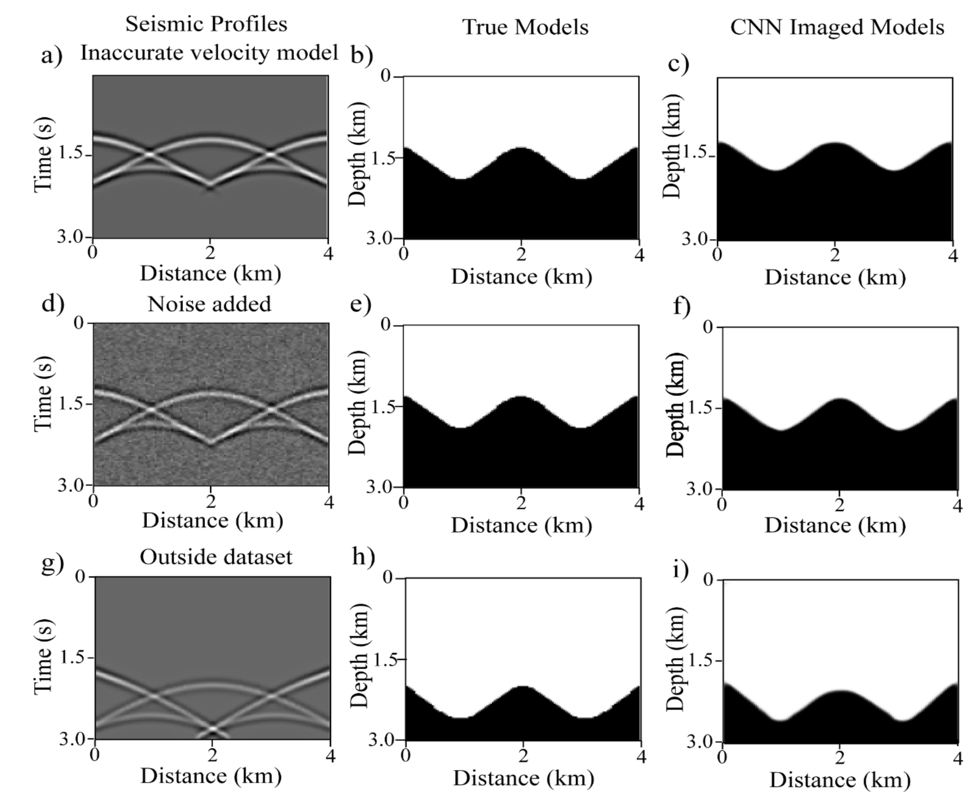
The binary accuracy, dice coefficient and binary cross entropy loss function of the CNN models with 8 starting kernels (filters) optimized by an Adam optimizer

Imaging Results from Trained CNN Model



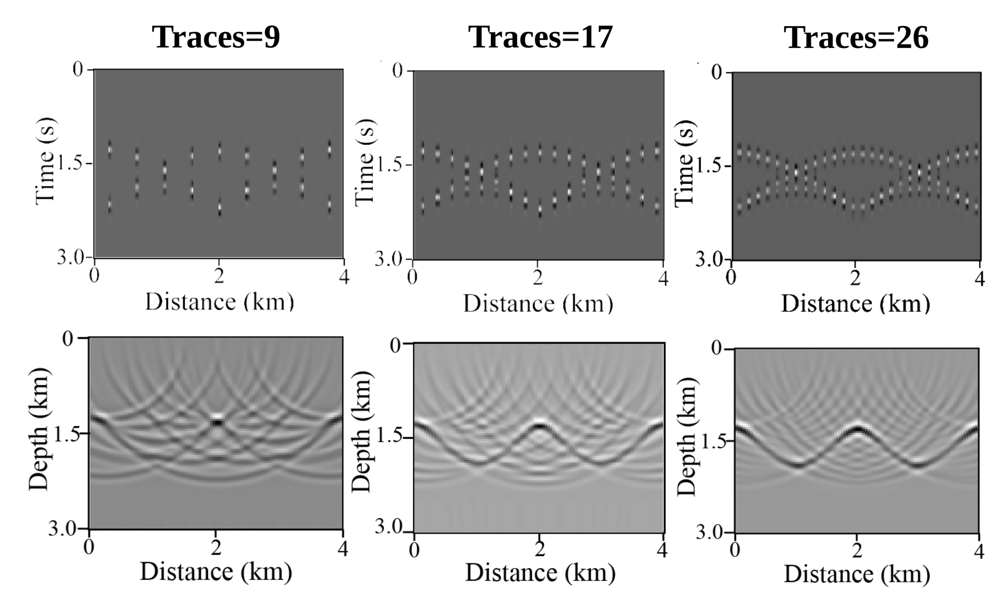
Imaged models from the trained neural networks. Subplots a), d), g) show the seismic profiles. Subplots b), e), h) are the true subsurface interface models and subplots c), f), i) are the corresponding imaged models predicted from the trained CNN model.

Imaging Seismic Profiles with Different Effects not Included in the Training Dataset



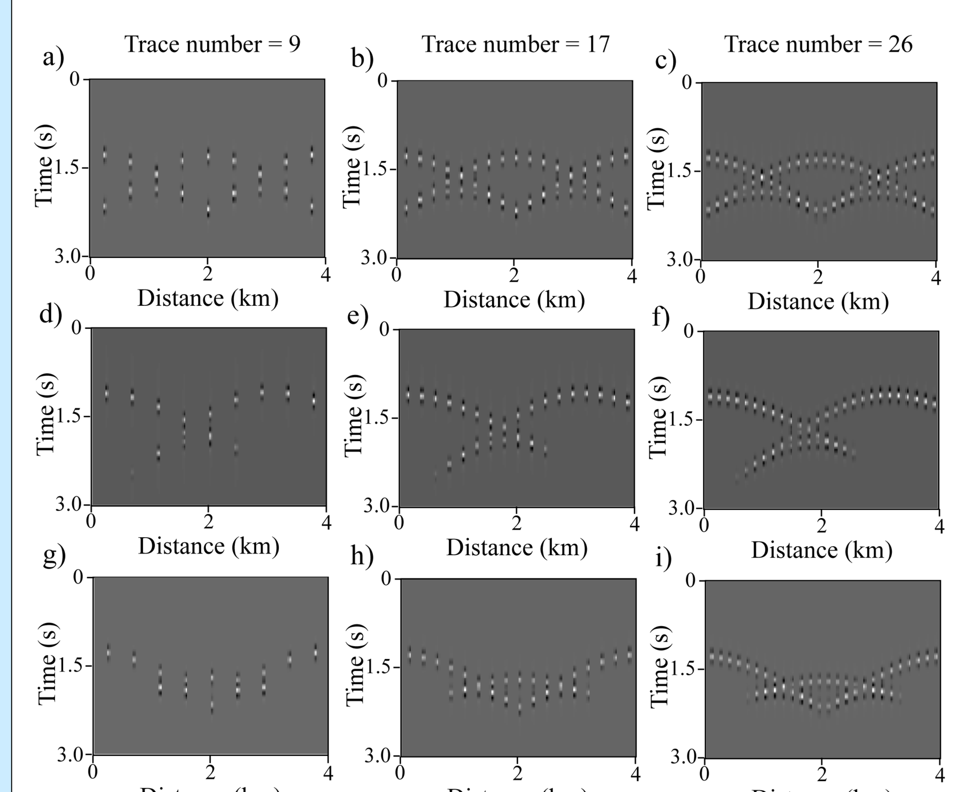
Imaged models from the trained neural network using seismic profiles with different effects not included in the training dataset. a)-c) The upper layer velocity of the model is 10% higher than model used for the training dataset. d)-f) 10% Gaussian noise is added to the data. g)-i) The seismic profile with an interface 0.7 km deeper than the training dataset.

Imaging Results using Stolt Migration for a Sparse Number of Traces



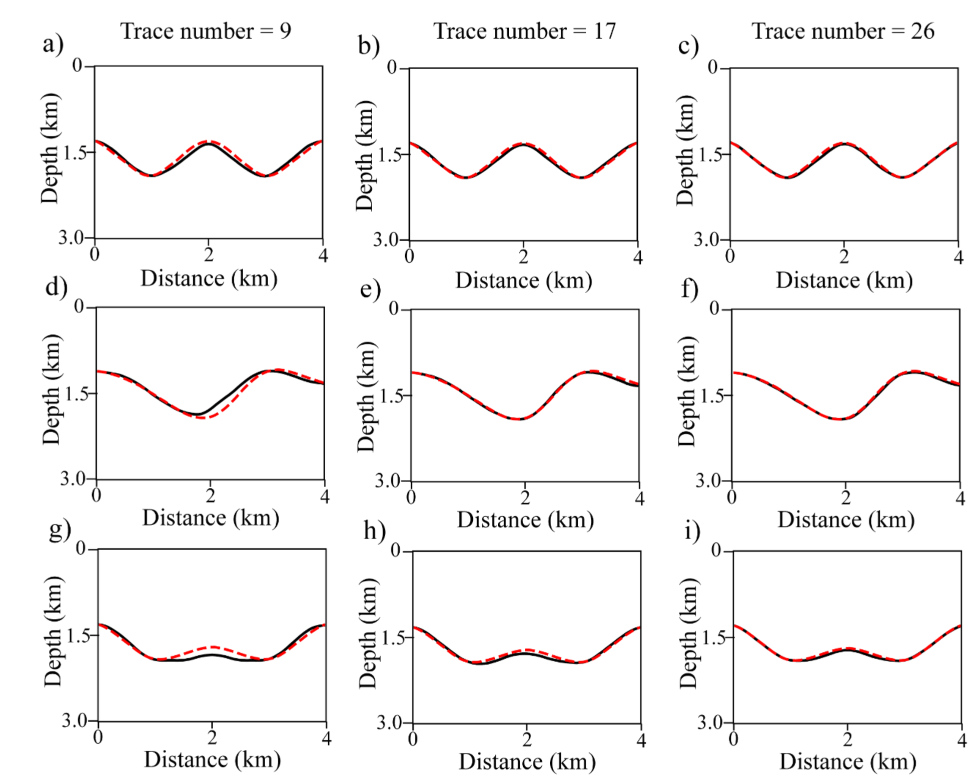
Seismic profiles with a sparse number of traces (above), and the resulting migration results (below).

Seismic Profiles with a Different Number of Seismic Traces



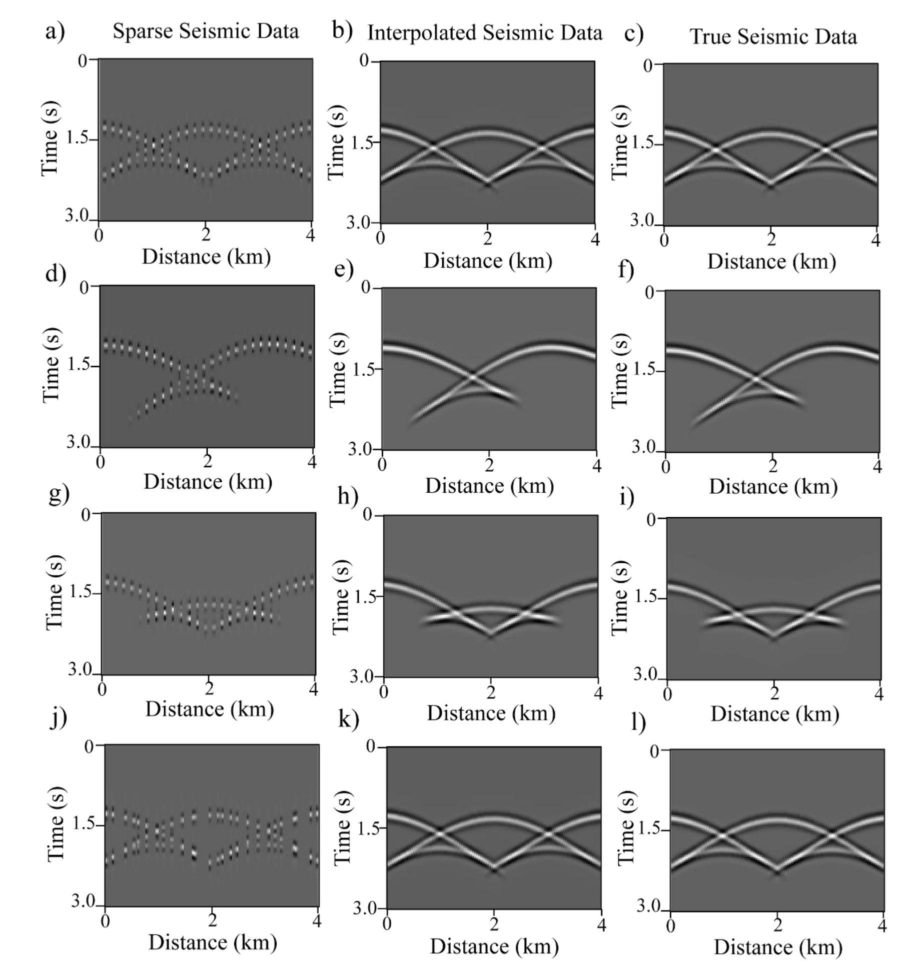
Several seismic profiles with a different number of seismic traces. Subplots a), d), g) are seismic profiles when the number of seismic traces is 9. Subplots b), e), h) are seismic profiles when the number of seismic traces is 17. Subplots c), f), i) are seismic profiles when the number of seismic traces is 26.

Imaging Sparely Sampled Seismic Profiles using a Trained CNN Model



The CNN imaged models when the number of seismic traces is 9, 17 and 26, respectively, and compared with the true models. The solid lines are CNN imaged models and the dashed lines are the true models.

CNN-based Seismic Trace Interpolation



Interpolated seismic data obtained using the CNN imaged results from the trained CNN model when the number of regular and irregular seismic traces is 26. a), d), g) are sparse seismic data when the number of regularly sampled seismic traces is 26. j) is the sparse seismic data when the number of sampled seismic traces is irregular. b), e), h) and k) are the interpolated seismic data from the CNN imaged models, and c), f), i) and l) are true seismic data when the number of traces is 101.

Conclusions

Convolutional neural networks have the potential of providing improved imaging results compared with traditional migration imaging methods when the spatial sampling of the seismic data is sparse. The CNN model is robust to the small variations from the training dataset. Since CNNs are a kind of supervised learning, the parameters of the CNN model are trained based on the most important features from training dataset. If the CNN model can still perform well for the real seismic data, which are much more complex, then it can greatly reduce the amount of data required for seismic imaging and at the same time be used to interpolate sparse data to a finer grid.

Acknowledgements

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