Velocity model building from one-shot VSP data via a convolutional neural network

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Summary

Velocity model building is an essential step in seismic exploration, which runs through the whole process of seismic data acquisition, processing, and interpretation. The velocity information is conventionally obtained by iterative optimization methods such as full-waveform inversion or tomography. These traditional methods are computationally expensive, and they require an initial velocity model and human interactions. To simplify the model building problem, we develop a supervised end-to-end conventional neural network to reconstruct the P-wave velocity models directly from raw seismic data. The network takes in one-shot seismic traces simulated with acoustic wave equations in VSP geometry. To train the network, we create 870 2D synthetic seismic images and corresponding labeled images, which are shown to be sufficient for the network to learn the nonlinear relationship between one-shot seismic data and the corresponding velocity model. The numerical examples show that the trained network is capable of predicting accurate layered velocity models from only one-shot seismic data.

Introduction

VSP plays an important role in reservoir prediction and description. With the characteristics of accurate depth and near reservoir observation, VSP data can help provide accurate velocity information and time-depth relationship, improve the accuracy of surface data imaging processing, and provide reliable position and depth of geological body for drilling targets (Mao et al., 2018).

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Accurate velocity models are perquisites for reverse time migration and other seismic imaging and interpretation techniques (Baysal et al., 1983). Conventional methods such as tomography, full-waveform inversion (FWI), and migration velocity analysis are often applied to address the nonlinear inverse problem of velocity model building. Although these traditional approaches can derive accurate velocity information in many applications, they are time consuming and computationally expensive, and dependent on the initial velocity model and sometimes human interactions. Therefore, an efficient, robust, and accurate velocity determination technique is appealing.

Many efforts have been made to estimate velocity models directly from prestack seismic traces using machine-learning (ML) technologies. For example, Araya-Polo et al. (2018) perform velocity model building with the semblance of common-midpoint gathers using a deep neural network. Yang and Ma (2019) develop a fully convolutional neural network (FCN) for salt-detection and subsurface velocity reconstruction from raw seismic data and the results are encouraging. Wang and Ma (2020) propose a VMB-net to estimate P-wave velocities in a crosswell acquisition. The trained network shows acceptable predicted results with the input of new prestack seismic data.

In this study, we focus on velocity model estimation directly from one-shot seismic data in VSP geometry using a modified U-Net, which was first proposed by Ronneberger et al. (2015) for biomedical image segmentation and then was widely applied to many other image segmentation problems. The shot is at the surface and receivers are in a well. This could be a shot gather from a walkaway VSP or from a 3D VSP dataset. This velocity inversion network consists of two stages. During the training stage, one-shot seismic data are fed into the network, which can effectively and automatically learn the nonlinear relationship between the seismic data and the corresponding velocity model. During the prediction stage, the trained network is capable of estimating the velocity models with new seismic images.

The paper is organized as follows, we first illustrate the network architecture for subsurface velocity reconstruction in detail. Then the data preparation and synthetic tests are presented to evaluate the inversion performance of our proposed network. Besides, the comparison of velocity versus depth profiles at 500 m offset between the predictions and the true velocities are shown to quantitatively analyze the accuracy of the predictions. The synthetic examples demonstrate that our proposed network for velocity model estimation is reliable, accurate, and efficient.

Method

We perform velocity model building by modifying the original U-net architecture (Ronneberger et al., 2015), which is proved to be effective for solving the nonlinear velocity model inversion problem. Different from the original U-Net architecture whose input and output are in the same domain, we transform the data from time domain (input) to depth domain (output) and turn the channel of the output layer to one.

Figure 1 illustrates the detailed convolutional neural network (CNN) we used in our velocity model building problem, in which an input 2D seismic image is fed into the network that consists of a contracting path (left) for extracting the geologic features and an expansive path (right side) for accurate velocity estimation. The original seismic image with the size of 200×2000 is first resized to 200×600,

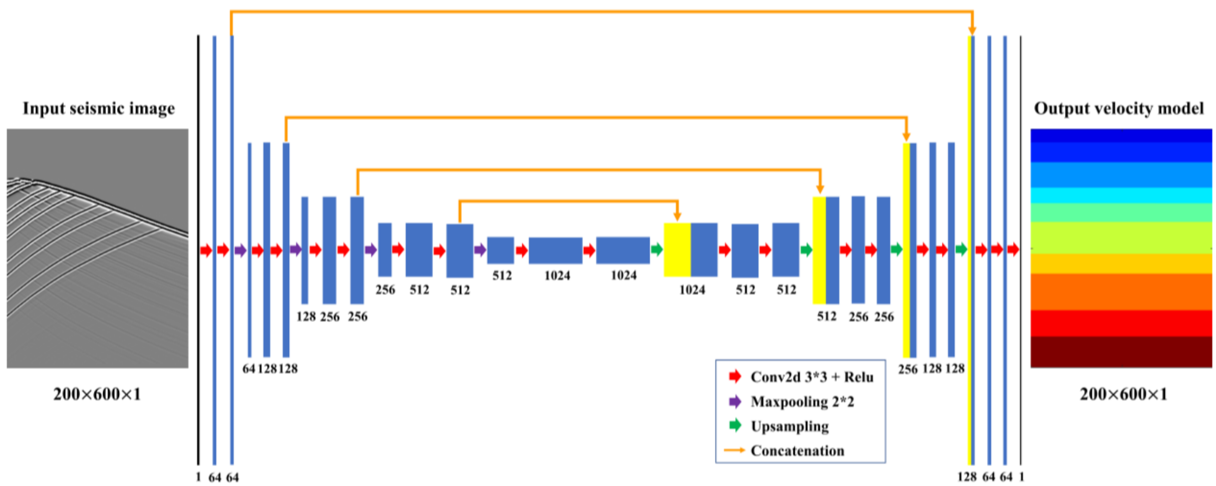

Figure 1: A modified convolutional neural network (U-Net) for 2D velocity model building.

which has the same size as the output velocity model. Then the resized seismic image is fed to the CNN network. As shown in Figure 1, each step in the left contracting path includes two 3 × 3 convolutional layers, followed by a ReLU activation and a 2×2 max-pooling operation with a stride of 2 for downsampling. In the right expansive path, each step contains a 2 × 2 up-convolutional layer and two 3 × 3 convolutional layers followed by a ReLU activation. Concatenation is used to combine the high-resolution features from the contracting path with the upsampled outputs from the expansion path. The main body of our network is similar to that of the original U-Net architecture and a total of 23 convolutional layers are included in this network.

The loss function represents the distance between the true velocity model and prediction. The loss function we used in the network is defined as the squared difference (L2 norm) between the predicted velocity model V^p and the ground truth velocity model V^t:

$$\mathrm{L} = \frac{1}{nx \times nz} \sum_{\substack{i=1,nx \\ j=1,nz}} [V_{ij}^t - V_{ij}^p]^2 \quad , \quad (1)$$

where nx and nz are the number of gird points in the horizontal and vertical directions, respectively. The true velocity information V^t is given during the training process but hidden during the prediction stage. Note that this loss function is different from that in the conventional FWI, in which the loss function calculates the squared differences between the observed and simulated seismic data.

Synthetic tests

In this section, we first present data preparation including input and output design for creating training and testing data sets. Then we test our proposed velocity model building network with synthetic data. We analyze the accuracy of the predictions by comparing the velocity versus depth profiles at 500 m offset between the predictions and ground truth.

1) Data preparation

To train an efficient network, a large amount of training data set and the corresponding labels are required. To create the training and testing data sets, we establish a total of 870 2D isotropic velocity models. We assign 708, 118, and 44 synthetic velocity models as the training, validation, and testing data sets, respectively. The velocity models are designed as parallel layers, either horizontal layers or inclined layers. Each of the models has 6-12 layers and the velocity values of each layer range from 2000 to 5000 m/s and increase with depth. All the velocity models have the same size that the x and z ranging from 0 to 1000 m and 0 to 3000 m with a grid interval of 5 m. For each model, only one shot is placed at 1 km offset and the 150 receivers are deployed from 10 to 2245 m in a vertical well, with a receiver interval of 15 m. We use the finite difference method to simulate seismic waveforms with a 30 Hz Ricker wavelet. The time interval is 1 ms and a total of 2000 time samples are recorded. Figure 2 shows three representative samples (a, b, and c) of the synthetic velocity model and their corresponding seismic images (d, e, and f).

2) Training and testing

The training time is related to the size of the seismic image, the number of training samples, and the complexity of the network. For this case, training 500 epochs took approximately 5 hours. Once the training stage is completed, the cost of the prediction of the network is negligible, with

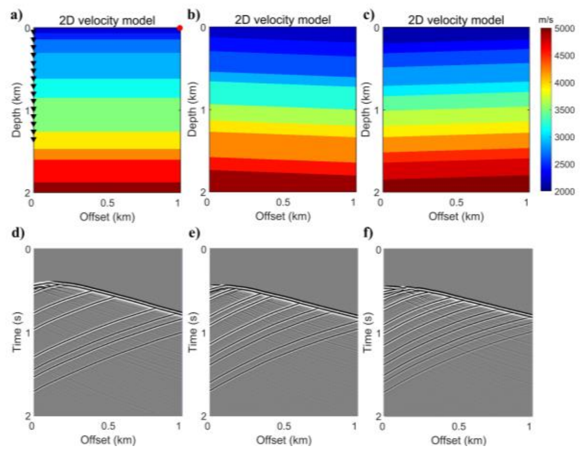

Figure 2: Three representative velocity models and their corresponding seismic images. The red dot denotes the source position and the black triangles indicate every 10th receiver (a total of 150 receivers).

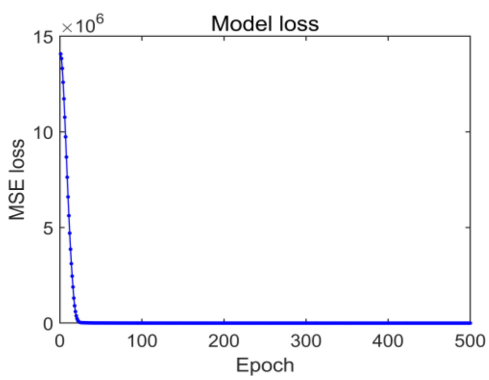

Figure 3: The training loss decreases with epochs.

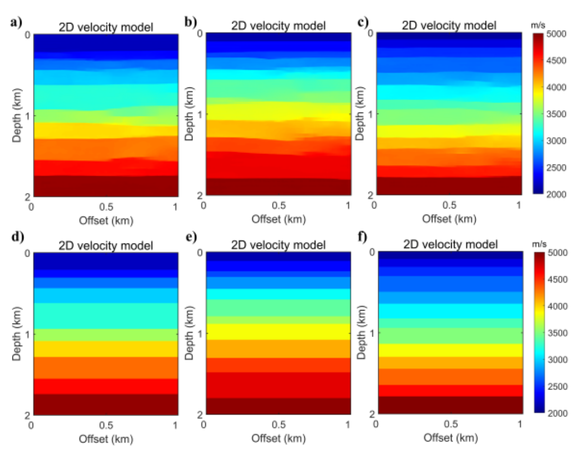

Figure 4: Comparison between the prediction of our method (a-c) and the ground truth (d-f) for the horizontal layered velocity models.

only a few seconds needed. Figure 3 shows the mean-squared error of the training data set, which converges to zero after 25 epochs.

To evaluate the inversion performance of our deep learning velocity model building network, we first test the 16 horizontal layered velocity models, which are not included in the training data set. Figure 4 shows the comparison between the predictions of our network (a, b, and c) and the ground truth (d, e, and f). All the subfigures have the same range of color bar, with the velocity values ranging from 2000 to 5000 m/s. As shown in Figure 4, regardless of the number of layers, the predictions successfully recover all the parallel velocity interfaces with accurate depths and velocities. Most velocity interfaces are depicted continuously and clearly, which are consistent with the ground truth. Although the third layer of the middle-velocity model (Figure 4b) is very thin compared with other layers, it is described clearly and accurately by our proposed network.

To quantitatively analyze the accuracy of the predictions, we present the predicted (blue line) and true velocities (red line) in the velocity versus depth profiles at 500 m offset. Figure 5 shows the vertical velocity profiles corresponding to the three velocity models in Figure 4. The predicted velocities of our network are in good agreement with the true velocities in both the values and depths.

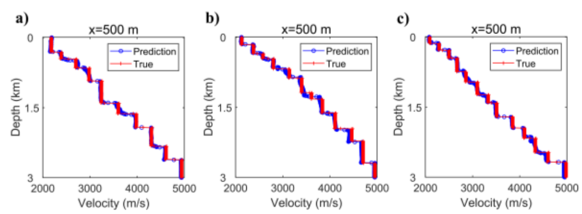

Figure 5: Vertical velocity profiles for the three test samples in Figure 4. The predicted and ground truth velocities in the velocity versus depth profiles at 500 m offset are presented.

To further validate the capability of our proposed network, we test it with the inclined parallel layered velocity models, which are not included in the training data set and are unknown during the prediction stage. Figures 6 and 7 show the comparison between the predicted results (a, b, and c) and ground truth (d, e, and f) of six velocity models with inclined layers. The inclined parallel velocity interfaces are recovered satisfactorily with high continuity and high accuracy in depths, velocities, and inclined angles.

Similarly, we plot the predicted velocity values and the true velocity values in the velocity versus depth profiles at 500 m offset to analyze the prediction accuracy as shown in Figure 8, in which the three upper profiles (a, b, and c) and the three lower profiles (d, e, and f) correspond to the velocity models in Figure 6 (a, b, and c) and Figure 7 (a, b, and c), respectively. There is a good match between the predicted velocity values and the ground truth for the parallel layered velocity models with inclined angles.

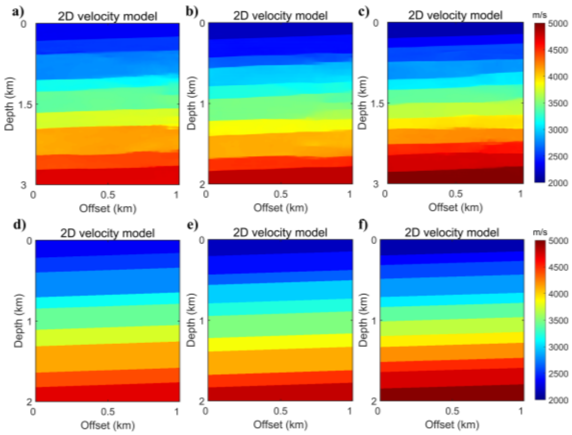

Figure 6: Comparison between the prediction of our method (a-c) and the ground truth (d-f) for the inclined layered velocity models.

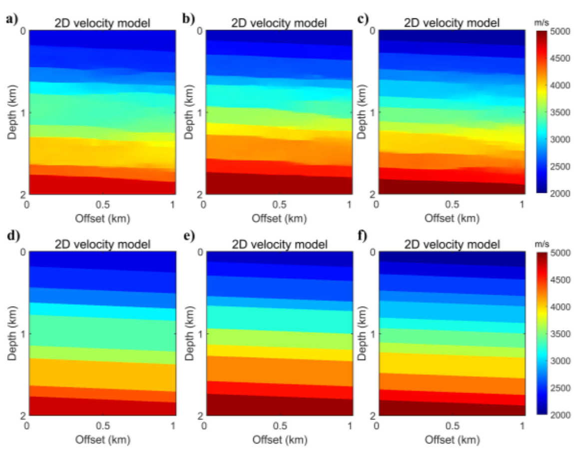

Figure 7: Comparison between the prediction of our method (a-c) and the ground truth (d-f) for the inclined layered velocity models.

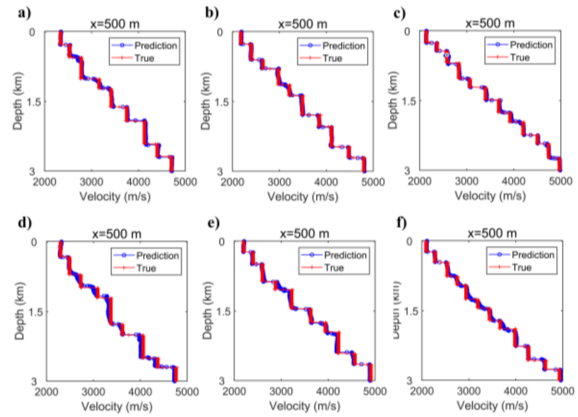

Figure 8: Vertical velocity profiles for the six test samples in Figures 6 (a-c) and 7 (d-f). The prediction and ground truth velocities in the velocity versus depth profiles at 500 m offset are presented.

Conclusions

In this study, we explored a supervised end-to-end convolutional neural network for velocity model building from one-shot seismic data recorded with VSP geometry. The network is modified from the original U-Net architecture and is applicable to solve the nonlinear problem of velocity model reconstruction. During the training process, the network takes in 2D seismic images and automatically extracts useful features of the nonlinear projection between the seismic data and the corresponding velocity model. Once the training stage is completed, the network is capable of estimating the velocity model with new input seismic data, and no initial velocity model or human intervention is involved. Although the training process is computationally expensive, the cost of the prediction is negligible once the network training is completed, with only a few seconds needed. The synthetic tests show promising performance of the proposed network. Both the horizontal and the inclined parallel velocity interfaces can be continuously and clearly recovered with accurate depths and velocities. The velocity-depth curves of the predictions and the ground truth at 500 m offset are in good agreement.

Acknowledgments

We thank financial support from China Natural Science Foundation (41674120). We would like to appreciate GeoTomo Hefei for the support of our study, allowing us to use VECON software to perform our research.