Characterizing the near surface velocity structures by applying machine learning

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Summary

The land and shallow marine data processing often encounters the challenges of the near surface complexity. If characterizing the near-surface structures through scanning seismic data could estimate the structure complexity by telling layered, gradient, or velocity reversal structures under each shot or receiver point, then such information could help design strategy for the selection of methods and parameters for the first-break picking and structure imaging. In this study, we develop a near-surface characterization method based on the Convolution Neural Network (CNN), a machine learning approach. The method automatically identifies several pre-defined model types from shot or receiver gathers, and it includes two steps: training and prediction. In training, a CNN model is trained with annotated seismic gathers, which are labeled as three types: layered, gradient, and complex velocity models. In prediction, the trained network is applied to determine the velocity model type from the input shot or receiver gathers. We demonstrate the effectiveness of the new method using synthetics and a real dataset acquired from Daqing, China.

Introduction

Near surface complexity could significantly affect oil and gas exploration in many ways, directly affecting the cost and the results of the efforts (Taner et al., 1974). In particular, today’s seismic data is very large, and it may require substantial time and resources to examine any information in the data. For processing land seismic data, it is also hardly to apply any universal workflow to all datasets (Yilmaz, 2001). Every area or region may present different geological settings. Repeated processing of a dataset without truly understanding the nature of its geological problem could be costly and time-consuming. Therefore, prior to any effort, identifying the type of near surface velocity structures under the data coverage area is helpful for planning strategies in dealing with seismic data processing and imaging, especially, if the method is performed automatically without any human interference.

In seismic wave propagation, a shot gather is the response of the near surface and subsurface structures, and the first arrivals are generally related to the near surface structures. One can visually recognize the fundamental near surface structure information from the first arrivals, for example, a layered velocity model consisting of increasing layer velocities with depth. One can also identify a gradient velocity structure, which produces a smooth curved first arrival in a shot gather. If the near surface structure is complex, consisting of velocity reversal, sink holes, and other anomalies in the near surface, then the first arrival of a shot gather should exhibit a complex pattern. Any moderate level of processing geophysicists should be able to characterize the nature of the near surface structures from visually examining the shot gathers. Unfortunately, this is too costly and time consuming since any real seismic data could easily include over 20,000 shots. The emerging Machine Learning (ML) technology motivates us to develop a more effective and efficient approach.

Machine learning offers algorithms designed to learn the features and relationships hidden in large datasets (Jia and Ma, 2017). ML has been widely applied in many fields in recent years (Nasrabadi, 2007). Deep Learning is a branch of ML based on a set of algorithms that attempt to model high-level abstraction in data. As one of the deep learning methods, the Convolutional Neural Network (CNN) has been intensively and broadly applied to identify faces, objects, traffic, and recognizing speeches (Abdel-Hamid et al., 2014; Jin et al., 2014; Li et al., 2015; Cheng et al., 2016).

The CNN has been applied to seismic data processing and interpretation, such as permeability prediction from the binary segmented images (Srisutthiyakorn, 2016), geologic features identification from seismic attributes (Huang et al., 2017), and prior models building from seismic images for full waveform inversion (Lewis and Vigh, 2017). In this study, we apply the CNN method to identify and characterize the near surface velocity structures from shot gathers. Once the training for mapping between shot gathers and velocity model types is completed, the input shot gathers can be processed by the trained network. The training task takes a few hours, but the inference effort takes only seconds for assessing a shot gather. Since the features of the training data for this purpose are actually global, that is, not associated with any particular region, it is not necessary to train the system again when applying the method to another dataset or another area.

We apply the method to both synthetic data and a real dataset acquired in Daqing, China. The full waveform inversion (FWI) method is applied to the Daqing data to obtain the complex near surface long-wavelength statics.

Method

The CNN for the near surface velocity structure characterization consists of two steps: training and prediction. The shot gathers for training and prediction are...
preprocessed by selecting a shot-receiver offset, muting, and applying linear moveout (LMO).

We formulate the near surface velocity structure characterization problem as an image classification task. Selected and processed data from each shot gather are divided into a 300×200 pixel matrix as a sample. The amplitude is normalized in the sample. The samples are labeled as three types: 0: layered velocity structures; 1: gradient velocity structures; 2: complex velocity structures. Figure 1 shows the training data samples, which include synthetics and real data examples. The synthetic data are calculated with a series of designed model structures, and the real data are acquired from Sichuan, China.

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The CNN is applied to the image classification task. Figure 2 shows the architecture of the CNN, which has two convolution layers (Conv). The first convolution layer has 30 2D convolution filters with the length of 3 elements in each dimension, the second convolution layer consists of 60 2D convolution filters with the length of 5 elements in each dimension. A max pooling layer (Pool) with both size and stride being 2×2 is applied after the first convolution layer. There are 120 and 84 feature maps in the two fully connected layers (FC), respectively. The prediction label which indicates the type of the input samples is produced in the output layer (Output).

The network is trained to minimize the mean square error (MSE) loss function. The MSE loss function is as follows:

\[
L = \frac{1}{n} \sum_{i=1}^{n} (C(x_i) - y_i)^2
\]

where \(x_i\) is the input sample, \(C(x_i)\) stands for the output of the CNN, \(y_i\) is the desired output, \(n\) represents the number of input samples for each iteration.

The learning rate is important for training. If the learning rate is too small, the training needs many epochs to acquire a good accuracy. If the learning rate is too high, the training will be unstable and not convergent. Figure 3 shows the training error curves with the different learning rates, we choose the trained network with the learning rate equal to 0.05 in this study.

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ML for near surface velocity characterization

**Synthetic test**

After training, we first apply the trained model to the synthetics. The shot gathers for prediction are obtained from a synthetic model. The geometry is designed as a rolling array, which includes 350 shots with a shot interval of 20 m and 200 receivers for each shot with a receiver interval of 10 m. Figure 4a illustrates the designed characterization of the shot line. It includes three types of near surface velocity structures: layered (blue), gradient (green), and complex (red). The shot gather examples for each type of structures is presented in Figure 4b.

![Figure 4: The synthetics](image)

**Daqing data example**

We process a real 2D dataset from Daqing, China. The geometry is designed as a rolling array, which consists of 476 shots with an average shot interval of 10 m and 474 receivers for each shot with a receiver interval of 10 m. The trace length is 6000 ms with a time-sample interval of 4 ms. The shot map of the geometry is presented in Figure 6a, each shot is marked by the black star.

The shot gathers for the prediction are preprocessed by selecting a shot-receiver offset, muting, and applying linear moveout (LMO). Each preprocessed gather is divided into a 300×200 pixel matrix. The samples of shot gathers in this area mainly consist of two types of velocity structures: layered and complex. The examples for each type of structures are shown in Figure 6b.

![Figure 6: The real datasets](image)

Figure 5 shows the near surface velocity characterization for the shot line by CNN, the model obtains 95% classification accuracy for the test. It is clear the most velocity structures are characterized successfully by the trained network although it has some wrong classifications nearby the characteristic interfaces.

![Figure 5: The near surface velocity characterization](image)

The trained model is next applied to the characterization of the near surface velocity structures for the real data. The prediction of CNN for the shot line is presented in Figure 7. It takes just a few seconds for assessing the whole shot gathers. The results show the study area consists of layered velocity structures between 2 and 5 km and complex velocity structures between 5 and 7 km. The results are consistent with the law of geological continuity although there are a few of discontinuous distributions.

![Figure 7: The near surface velocity characterization](image)
ML for near surface velocity characterization

Figure 7: CNN characterizations of near surface velocity structures for the Daqing shot gathers.

Full waveform inversion (FWI) can resolve complex near surface structures. Based on the characterization of CNN, we do the first-arrival traveltime solution for the entire model, and then further refine the complex area with FWI using a subset of data (Complex shot gathers). Figure 8 presents the FWI solutions for the near surface velocity structures.

Figure 8: The solutions of FWI based on the CNN characterization.

Figure 9 shows the long-wavelength statics based on the results of the FWI. The major statics of shots and receivers are found between 6 and 8 km, where the complex velocity structures shot gathers are characterized by CNN. The results indicate that the CNN model learns to distinguish different types of the near surface velocity structures.

Figure 9: Long-wavelength statics based on the FWI results. The solid line denotes the statics of receivers, and the dashed line denotes the statics of shots.

The CMP stacking result based on the FWI solutions is presented in Figure 10. The stacking velocities are picked separately for the corrected datasets. The lateral continuity of the reflectors indicates the effectiveness of the long-wavelength statics.

Figure 10: The CMP stacking result after long-wavelength static corrections using FWI solutions.

Discussions and Conclusions

In this study, the near surface velocity structures are classified as three types: layered, gradient, and complex. But this is a rough classification, the near surface structures are very complex, such as the hidden low velocity layers, which should be handled carefully with our method. The shot gathers of the hidden low velocity layers are labeled as the layered velocity structures in our method, but the hidden low velocity layers cannot be resolved by the conventional layered imaging method such as the first-arrival traveltime tomography. Actually, the hidden low velocity layers should be classified as a new type of velocity structure, which will be performed in our future work.

We apply the CNN method for near surface velocity structures characterization. The method consists of two steps: training and prediction. While the training task takes a few hours, the prediction step takes only seconds once the training for mapping between shot gathers and velocity model types is completed. The results of 2D synthetics and real data demonstrate the effectiveness of our method. The method can be applied to 3D datasets as well.

Acknowledgments

We thank the financial support from Major State Research Development Program of China under grant No. 2016YFC0601100. We appreciate the support from GeoTomo, who allowed us to use the TomoPlus software package to perform this work.