

Application of Convolutional Neural Networks for Seismic Velocity Model Building Using “Realistic” Synthetic Data

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Accurate interval velocity models are required for reliable depth migration of multichannel seismic reflection data. Current velocity model building methods, such as migration-based velocity analysis approaches, require a considerable amount of human interactions with several rounds of picking and model refinement which is time consuming. More advanced methods like full waveform inversion (FWI) can achieve a reasonable subsurface model in a semi-automatic manner with less user control, but their performance depends on several factors such as the accuracy of initial model, bandwidth of the seismic data, etc. We propose a method that can estimate the interval velocity models faster and more accurately by using convolutional neural networks (CNN).

The velocity model building with convolutional neural networks faces the lack of training data for various realistic problems, and one of the solutions is to use synthetic data in CNN model training. In the recently developed velocity model building tools, convolutional neural networks have proven to be effective for simple geological settings. However, in the more complex geologies such as subduction systems, CNN have a gap compared to traditional model building methods. To address this issue, we implemented a more complex synthetic model into our CNN training. The synthetic training dataset is generated by altering the “realistic” GO 3D OBS model (Górszczyk, A. and Operto, S., 2021). Our CNN model uses the residual velocity semblance panel as input data for training and the labels for each input are from the corresponding interval velocity profile at the same location. The whole dataset is split to training, validation, and test datasets.

In this study, we incorporate CNN into marine seismic data processing by using the residual velocity semblance panel and the corresponding velocity profile at each location as training data to train the CNN model. A simple pre-stack depth migration using a linear velocity helps to transform the problem to depth domain. Also, the vertical semblance profiles have a smaller data volume compared to the original shot gathers. Finally, the features of the data are easier to be learned by the CNN. Although the training requires computational resources, once the network is trained it can predict a reliable velocity model quickly.