Deep learning inversion of seismic data under various observation setups

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Abstract. Deep learning has recently drawn massive attention for the task of geophysical inversion because of its strong non-linear mapping ability, especially for seismic inversion. Many works have been proposed. However, to simplify the problem, most of researchers only consider the simple observation setup and regard the task as the directive mapping between seismic data and velocity model, which limits the application in the real scenario. To solve this problem, we adopt the recent proposed SeisInvNet, which reconstructs the velocity model by treating each seismic trace as the essential element. Furthermore, we further extend its encoder part to make it accept randomly sampled traces as input so that it can be suitable for the inversion of seismic data under various observation setups. By comparing with the inversion results, we find that the modified SeisInvNet not only can adapt to various observation setups but also performs slightly better than the original method.

1. Introduction
Due to the limit of observation data, the inversion of geophysics is ill-posed and non-unique. For this task, traditional inversion methods, such as full waveform inversion, still suffer from non-linearity and non-uniqueness issues. With the remarkable non-linear mapping ability, deep learning approaches have gotten more and more researchers’ favor. Mauricio Araya Polo [1] proposed an inversion network for seismic data based on the deep neural networks (DNN), which was trained by tens of thousands of randomly generated velocity models and corresponding synthetic data pairs. And the inversion network performs better. Yu Wu [2] proposed the CNN-CRF model based on convolutional neural networks (CNN) and conditional random field (CRF), which dramatically improves the accuracy of velocity inversion while reducing the computational time. Fangshu Yang [3] used the full convolution neural networks (FCN) to carry out the seismic inversion and obtained satisfactory results; Shucai Li [4], proposed a novel and specific inversion network named SeisInvNet for the inversion of layered velocity models. In addition to seismic data inversion, deep learning has also done a great job in other geophysical inversion problems such as the inversion of apparent resistivity data [5] the inversion of ground penetrating radar data [6] and the inversion of 2-D magnetotelluric data [7].

However, all above work didn’t take the observation setups in to account. Observation setup is the arrangement of sources and receivers and it’s an essential factor for seismic inversion. In seismic data acquisition, researchers usually design different observation setups according to the actual situation of the survey area, which results in the uncertainty of observation setups. Therefore, for the same survey area, the seismic data maybe collected under various observation setups. What’s more, there are loss of seismic traces in a seismic profile caused by poor contact of instruments and other uncontrollable
factors. Both of them will impact the inversion effect of network. Therefore, in order to solve this problem, based on the proposed SeisInvNet model, we make further improvement to improve its flexibility and applicability.

2. Methodology

The problem of seismic inversion can be reduced to the problem of solving equation (1):

\[ m = G^{-1}d \]  

(1)

Where \( m \) is the geological model, \( G^{-1} \) is the mapping operator, and \( d \) is the seismic data. The conventional ways to address this ill-posed seismic inversion problem is by iterative algorithms, which suffer from non-linearity and strong non-uniqueness. With the powerful non-linear mapping ability, deep learning can alleviate these problems and gain a better inversion result. Shucai Li [4] proposed an end-to-end seismic inversion networks named SeisInvNet which takes DNN as the main network framework. The SeisInvNet can enhance seismic traces with its neighbor information observation setup and global context. And then it can learn the spatially aligned feature maps which are helpful to the reconstruction of velocity from enhanced seismic traces. The SeisInvNet overperforms the conventional methods both on the accuracy and speed of inversion.

The SeisInvNet take observation setups corresponding to seismic data into account. It uses one-hot vector to record observation setups. To reduce the computational complexity, they only considered a kind of fixed observation setup. In their study, the experiment of discarding the random traces data is discussed, which proves the applicability of SeisInvNet when seismic traces missed. However, for more abundant observation forms and larger receiver changes, further improvements are still needed. In order to solve this problem, we modify the SeisInvNet from two aspects, seismic data extraction method and one-hot vector. As a result, it can be suitable to the seismic inversion under various observation setups.

![Image](image_url)

**Figure 1.** (a) The original seismic profile. (b) The seismic profile sampled uniformly. (c) The seismic profile sampled randomly.

In our dataset, one seismic profile contains 100 traces (as shown in figure 1a). To reduce the computation complexity, SeisInvNet extracts 32 seismic traces uniformly from a seismic profile (as exhibited in figure 1b). We have made some improvements in this part. For each seismic profile, we extract 32 seismic traces randomly and get different seismic profiles under various observation setups. As demonstrated in figure 1c, for the direct wave, the random selection of the traces destroys the continuity of the direct wave, for the reflected wave, its shape could be generally preserved, but with slight local distortion (remarked by red circle). In order to correctly encode the information of observation setup, we use a larger one-hot vector (A vector with 0 everywhere, except the position
corresponding to the position of the receiver or source, and this position is marked by 1.) As shown in Figure 2, the size of one-hot vector that encodes the information of receivers expand from 32 to 100. In this way, the improved method can provide sufficient observation setup information for the network and solve the problem of changing observation system.

3. Experiment

3.1. Dataset preparation and Experimental Setting

We used the same dataset as the SeisInvNet used for training. There are 12,000 different velocity models and the corresponding synthetic seismic data pairs in our dataset. And we divided into three sets that 10,000 for training, 1,000 for validation, and 1,000 for the test. Specifically, we randomly created four types layered velocity models, named type I, II, III, and IV, respectively, according to the number of underground interfaces. The velocities of these models varying from 1500 to 4000[m/s].

What's more, In the forward numerical simulation of wave equation, these models are divided into 100 * 100 grid points. On the surface of velocity models, we set 20 seismic sources with five grids interval and 100 receivers on every grid.

3.2. Qualitative Comparison

In this subsection, by comparing the performance of SeisInvNet and modified SeisInvNet on the four examples randomly selected from the test set, we will verify the effectiveness of the modified SeisInvNet.

As shown in Figure 3, through the comparison of the first and second columns of images, it can be seen that the modified SeisInvNet can accurately reconstruct the velocity field. As exhibited in the velocity profile, the velocity field reconstructed by modified SeisInvNet is basically the same as that of ground truth. But we can also find that with the increase of depth, the prediction accuracy is lower. This make sense. It is difficult to obtain sufficient information about the deep formation, so the inversion accuracy cannot be guaranteed. Comparing the results of the modified SeisInvNet with that of the SeisInvNet, as shown in the second and third columns in Figure 3, the modified SeisInvNet is better at velocity reconstruction than SeisInvNet. But it is insensitive to the slight changes on the interface. As remarked by the red circle, SeisInvNet successfully reconstructs the small bump on the second interface while the modified SeisInvNet almost missed this structure.

What's more, to verify the inversion effects of the modified SeisInvNet, we use the same metrics as Shucai Li et al. (2019) used. The results are shown as follows:
Table 1. Performance statistics of modified SeisInvNet and SeisInvNet on the five metrics

| Metrics   | Modified SeisInvNet | SeisInvNet |
|-----------|---------------------|------------|
| MAE ↓     | 0.014962            | 0.013870   |
| MSE ↓     | 0.001226            | 0.001002   |
| SSIM ↑    | 0.95338             | 0.950964   |
| MSSIM ↑   | 0.9861              | 0.988085   |
| Soft Fβ   | 0.761035            | 0.768807   |

For each metric, the better results are highlighted in blue. And the ↑ indicates the larger value achieved, the better performance is, while ↓ indicates the smaller, the better.

From the statistical metrics, we can see the performance of the modified SeisInvNet on the test set is slightly better than that of the SeisInvNet. Compared with seismic data under a kind of fixed observation setup, that under various observation setups can provide more information for the network and improve the prediction accuracy. On the one hand, due to various observation setups, we can obtain more abundant and comprehensive underground information, then provide more accurate global information for the network. On the other hand, the way of randomly selecting seismic data traces reduces the interference of humans, so that the network can fully explore the mapping relationship between the synthesis seismic data and the corresponding velocity models. But, it also brings some problems. Because of the variable intervals within observation setups, the neighbor information of each seismic trace is weakened, which is helpless to reconstruct details. So, we can see that the modified SeisInvNet almost miss the small bump on the second interface of the third velocity model.

Figure 3. Inversion results of the modified SeisInvNet (the second column) and the SeisInvNet (the third column) as well as Ground truth (the first column) from the test set.
4. Conclusions
We improved SeisInvNet by modifying the one-hot vector and make the network suitable for the inversion of seismic data under more extensive observation setups. By comparing visual and statistical results, we find that the modified SeisInvNet overperforms SeisInvNet on the velocity reconstruction. In further work, we intend to adapt the SeisInvNet for the inversion of real seismic data.

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