A high-precision diffraction multiples suppression method based on the detection neural network

Introduction

In seismic exploration, in order to get better results on seismic interpretation, a set of seismic data with high signal-to-noise ratio (SNR) is of vital importance. With the development of seismic exploration, offshore exploration for oil and gas is becoming more and more common. However, in marine seismic data, multiple is one kind of noises that influence the subsequent processing steps. To attenuate the multiples in marine seismic data, numerous methods have been proposed. These methods can be divided into two classes, including filtering methods and subtraction methods. The filtering methods attenuate multiples in the transform domain, such as the F-K filter method and the Radon transform method. The subtraction methods deduct the predicted multiples from the noisy data, such as the surface-related multiples elimination (SRME) (Verschuur et al., 1991). The SRME method performs well in some marine seismic data, and this method has been applied in many commercial software.

The SRME method consists of two steps. The first step aims at predicting the multiples, and the second step consists of subtracting the detected multiples. The performance of the subtracting step is heavily dependent on the predicted multiples. However, when SRME method is applied to the data recorded on deep ocean floor with complicated and adverse circumstances, the diffraction multiples are hard to be predicted. If the amplitude or the phase of the predicted multiples is not the same as the true multiples in the original data, the subtracting step will lead to inaccurate results which will remain much diffraction multiples. Therefore, how to attenuate the residual diffraction multiples is an urgent problem in deep ocean exploration.

In recent years, deep neural networks have been widely used in geophysics. The NDA-CNN network was proposed for suppressing the high amplitude noise in seismic data (Zhu et al., 2019). A CNN based framework was proposed to attenuate the ground-roll by using inter-band morphological similarity and pattern coding (Jia et al., 2020). As for the seismic interpretation, the convolutional neural networks have been also used to get high-resolution reservoir predictions. (Xu et al., 2019). The Cycle-GAN, which circulates two generative adversarial networks, was used to mitigate the dependence of CNN on the amount of labelled data in seismic impedance inversion (Wang et al, 2019).

We propose a high-precision diffraction multiples suppression method based on a detection neural network. We first apply the SRME method to the original data to obtain the predicted multiples and the preliminary suppressing results. Then a detection neural network named Yolo v5 (Glenn et al., 2021) is employed to detect the residual diffraction multiples in the preliminary suppressing results. Utilizing the detection results, we can apply an adaptive subtraction method proposed by Jiang et al. (Jiang et al., 2020) to the detection regions and suppress the residual diffraction multiples. By using the detection neural network and the adaptive subtraction method, we can get the better results.

Method

The flow diagram of our method is shown in Figure 1.

![Figure 1 The flow diagram of our method, including training phase, detection phase and adaptive multiples subtraction phase.](Image)
As the shown in Figure 1, our proposed method can be divided into four steps. The first step consist of using the SRME method to generate the preliminary suppression results and the predicted multiples. Then we label the regions with diffraction multiples remaining. The second step is to use the previous data and the generated labels to train the Yolo v5. The third step is to apply the well-trained network to our testing data resulting in the detection of the regions with diffraction multiples remaining. The final step is to employ the adaptive multiples subtraction method which is based on an auto-encoder to suppress the residual diffraction multiples.

In the training and detection phase, the network we use is the Yolo v5 (Glenn et al., 2021). This is a one-stage object detection network. It is important to note that comparing to the previous versions of Yolo series, Yolo v5 has the much faster detection speed while the detection accuracy is nearly the same with that of the previous versions. Considering that there is always a large amount of data in seismic processing, we choose the fastest network in Yolo series. The loss function we use contains three parts, whose expressions are as follows,

$$\text{Loss} = L_{\text{box}} + L_{\text{obj}} + L_{\text{cls}}$$

Because there is only one class in our detection objects, the $L_{\text{cls}}$ is always zero.

$$L_{\text{box}} = 1 - \text{GIOU} = 1 - \left( \frac{|B_p \cap B_g|}{|B_p \cup B_g|} - \frac{|B \setminus (B_p \cup B_g)|}{|B|} \right)$$

where $B_p$ refers to the region detected by the network, and $B_g$ is the ground truth. $| \cdot |$ represents the area, and $B$ is the smallest enclosing convex object for $B_p$ and $B_g$. The content in the brackets is in fact the expression of GIOU (Rezatofighi et al., 2019). GIOU performs better as the loss for bounding box regression than the normal IoU.

$$L_{\text{obj}} = \text{BCELoss}(\text{sigmoid}(p), \text{GIOU})$$

where the expression of BCELoss with input $x_n, y_n$ is as follows:

$$\text{BCELoss} = -\frac{1}{n} \sum (y_n \times \ln x_n + (1 - y_n) \times \ln(1 - x_n))$$

In adaptive multiples subtraction phase, we use the PCA-based auto-encoder (Jiang et al., 2020) to extract the features from the predicted multiples and reconstruct the residual diffraction multiples in the preliminary results. The feature extraction process can be regraded as solving the following optimization problem:

$$B = \arg \min_{B^T B = I} \| M - BX \|_2$$

where $M$ donates the patches of predicted multiples in a matrix form, and $X$ donates the feature vectors. $B$ is the projection matrix whose columns represent the learned patterns. The residual multiples reconstruction process can be regraded as the operation of solving the following optimization problem:

$$Y = \arg \min_{Y} \| S - BY \|_1$$

where $S$ donates the patches of the preliminary suppression results in a matrix form, and $Y$ donates the determined codes whose columns represent the optimal coefficients to reconstruct the residual diffraction multiples in $S$. The final diffraction multiple suppression results $P$ are obtained as follows:

$$P = S - BY$$

The overall process of the adaptive multiple subtraction phase is shown in Figure 2.

**Figure 2** The overall process of the adaptive multiple subtraction phase.
Examples

**Figure 3** The training loss and the result of field data. The left figure is the loss curves during the training and validation processes, respectively. The right figure is the detection result of the network on testing data. The red boxes in the right figure are the detected regions with residual diffraction multiples.

**Figure 4** The suppression results of a patch after the adaptive multiple subtraction phase. (a) is the predicted multiple, (b) is the (a) after removing reflection waves, (c) is the low frequency of (b), (d) is the preliminary suppression result, (e) is the (d) after removing reflection waves, (f) is the low frequency of (e). (g) is the final result, (h) is the (g) after removing reflection waves, (i) is the low frequency of (h).
We applied our method to the marine seismic data coming from south China sea. Figure 3 shows the loss curve during the training and validation processes and the detection results of the network on testing data. From the analysis of the loss curve, we can see that the loss in both training set and validation set becomes more and more smaller, which shows that the network converges well. In the detection result, the data we use is the original data after SRME and removing the reflection waves. All the red boxes in right figure contain the residual diffraction multiple.

Figure 4 shows the suppression results of a patch after the adaptive multiple subtraction phase. The first row is the predicted multiples. The second row is the preliminary suppression results. The third row is the final results. We can see that the adaptive multiple subtraction method performs well. The residual diffraction multiples pointed by the red arrows are well suppressed, and the final results hardly contain them. To show the effect of the suppression method, we also show the results after removing the reflection waves (the second column in Figure 4) and the low frequency of the second column in Figure 4 (the third column in Figure 4). Our method not only suppresses the residual diffraction multiples well, but also preserves the signals. Owing to the fact that we only apply the adaptive multiple subtraction method to the detected regions, the signals in other regions will not be affected.

Conclusion

In this article, we propose a high-precision diffraction multiples suppression method based on a detection neural network. Our method first detects the regions with residual diffraction multiples in the data processed by SRME, and then applies adaptive multiples subtraction method to these regions. Compared to the conventional methods, our method can not only suppress the diffraction multiples better but also do less harm to signals. The results on the field data also demonstrate that our method is effective and practical.

Acknowledgement

This work was supported in part by the National Key Research and Development Program of China (Multivariate Information Compatibility Expression via Artificial Intelligence) under Grant 2018YFA0702501, in part by the Natural Science Foundation of China under Grant 41974126 and Grant 41674116.

References