

MULTIPLE ATENUATION IN SHOT GATHER BY USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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Abstract. Today Machine Learning is used in almost every field for human life, including geophysics. Some examples of Machine Learning utilities are classifying lithology and predict petro physical parameters based on several supported data. Especially in seismic method, Machine Learning can be used for removing or attenuate multiple from seismic image or shot gather data by using Convolutional Neural Network (CNN). It reduces the multiple from shot gather data (input) based on filtered shot gather data (called by ground truth model) as the label or target. Unfortunately, filtering process sometimes erase boundaries layer in shot gather. Then CNN works by generating several activation function in neurons and hidden layers, multiply with input data and reconcile them to labels to reinforce the boundaries. To validate the CNN result, it can be seen from L – curve as the loss function that represent the prediction error. The fewer the prediction error, the more accurate result is observed.

Keywords: Shot gather, Multiple, Ground Truth, Machine Learning, Convolutional Neural Network

INTRODUCTION

Seismic method is a common way that used by geophysicist for describing the subsurface. It describes seismic wave propagation from a source (like dynamite) to geophone or receiver through the subsurface. If there are several layers in the subsurface, seismic wave can be reflected, refracted or transmitted. However, seismic method is still powerful in determining Oil and Gas potential. There are three important things in seismic method, they are, acquisition, processing and interpretation. Acquisition step consists of field observation or getting the data from research area. Processing aims to increase the performance of subsurface description or optimizing the subsurface model. While interpretation, analyze the result that coming from processing step and make sure that it is suitable to the geological condition (Rodriguez *et al.*, 2023; Gonzalez, 2024).

Seismic method can be done both in land and ocean (marine seismic). In marine seismic, geophone is replaced by hydrophone. Seismic wave is very susceptible to noise contamination. Noise is unwanted signal that can come from several factors. It can be caused by layer heterogeneities or by influencing of sea current. But in general, noise is divided into two categories, inherent and coherent noise. Inherent noise represents low correlation between two channels (geophone or hydrophone), usually occurs in marine seismic. Meanwhile coherent noise occurs when wave propagation is disturbed, for example, when seismic wave pass through the water in the subsurface, it will lose the energy, resulting a weakening in wave propagation (Sun, 2022).

The seismic data then collected based on the same source, called shot gather (Bucker *et al.*, 2019). If a Multiple exists, it can appear clearly in shot gather and make the interpretation becoming hard. Figure 1 shows the example of multiple in shot gather.

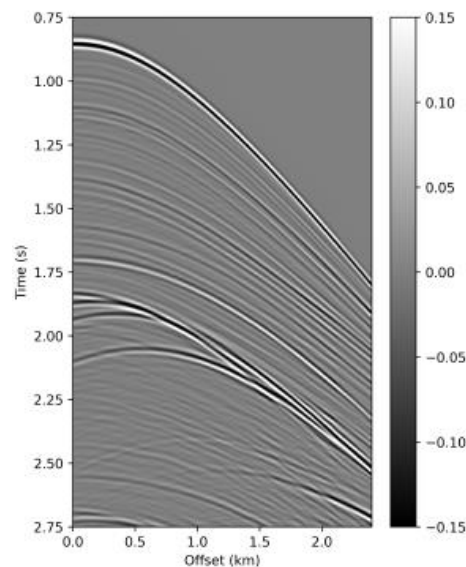


Figure 1. Shot gather with multiple (Kiraz and Snieder, 2022)

Unfortunately, removing multiple from shot gather is difficult. The manual way that has been done for solving this problem is by filtering, for example, SRME (Surface Related Multiple Elimination). Multiple is identified by frequency value, then separated from seismic data (Kiraz and Snieder, 2022). There are several ways to filter shot gather data. Two example are FK filter and apply general filter trace by trace in shot gather (Kiraz and Snieder, 2022). F-K filter transforms the shot gather into wavenumber and frequency domain by applied 2D FFT (Rodriguez *et al.*, 2023). Then, filtered shot gather data is called ground truth.

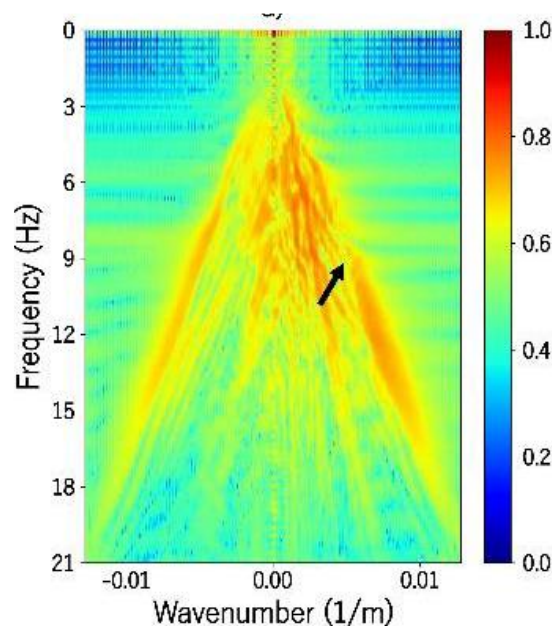


Figure 2. Result of 2D FFT in shot gather data. The color spectrum represents the magnitude of seismic trace modified from (Rodriguez *et al.*, 2023)

Although filtering multiple from shot gather is quite challenging, but it should be done for improving seismic interpretation. Several researchers then using Machine Learning to make it fast and easier. Convolutional Neural Network (CNN) is an example of Machine Learning. It identifies multiple based on the database. The database consists of example data called data train and its label. In this case, data train is shot gather itself, while the label is ground truth of filtered data (Slang *et al.*, 2019; Kiraz and Snieder, 2022; Rodriguez *et al.*, 2023).

Besides for neglecting the multiple, some researchers use Machine Learning for determining the quality data and reconstruct shot gather. Bucker *et al.*, (2019) classify shot gather into three criteria, good, bad and ugly shot gather data using CNN. In this case, the criteria represent the label. While, Huff *et al.*, (2023) use CNN to reconstruct the missing data in shot gather like in Figure 3.

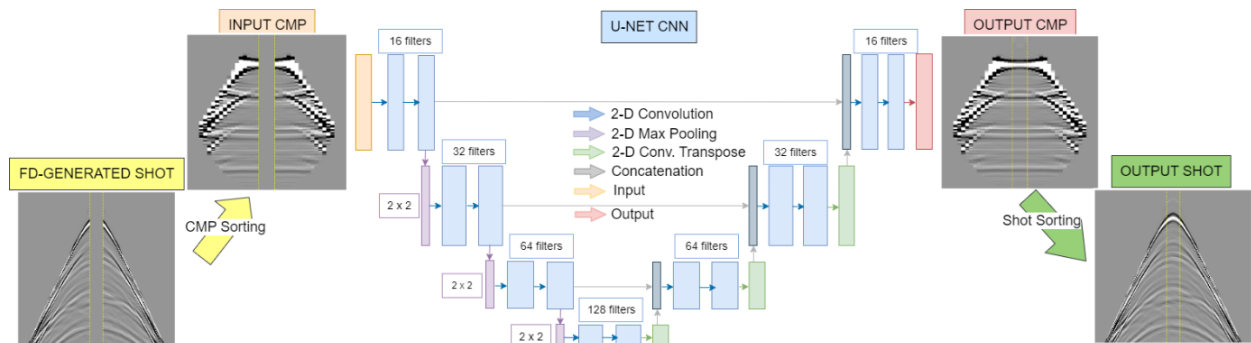


Figure 3. Shot gather missing data reconstruction by using CNN modified from (Huff *et al.*, 2023)

Figure 3 shows the workflow of CNN. Starting by identifying the data train and its label, multiplying activation function and the input data then optimizing to get the best result. In this paper we will do the similar thing with Kiraz and Snieder (2022) to remove the multiple from shot gather data. We adopt devito for generate our own geological model and simulate seismic source and the geophone location for observing the shot gather (Caunt, 2021).

METHOD

Convolutional Neural Network (CNN) is a part of Machine Learning. In Machine Learning, a parameter will be classified or predicted, depends on input data and its label, and in Neural Network process, neurons are consisting of weighting and a constant that form activation function, multiply to the data, then, due to some optimization functions, one best model will be selected as an output with low prediction error (Sun *et al.*, 2020).

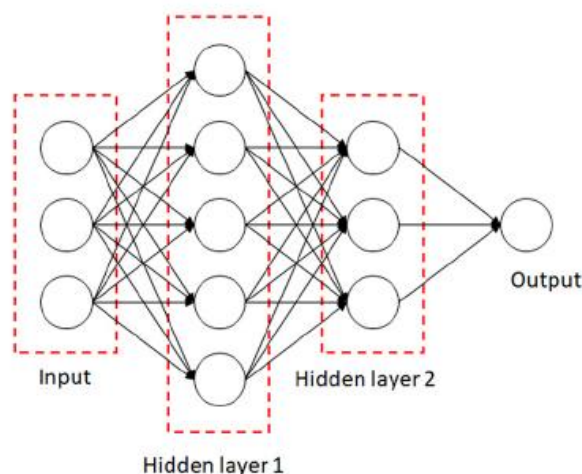


Figure 4. Convolutional Neural Network concept modified from (Teuwena and Moriakova, 2020).

According to Figure 4, a CNN architecture can have many hidden layers. Hidden layer is a place for collecting neurons. As previous mention that neurons contain activation function. Two examples of activation function are linear (T) and sigmoid (σ), represented in Equation (1) and Equation (2)

$$T = wx + b \quad (1)$$

$$\sigma = \frac{1}{1 + e^{-x}} \quad (2)$$

where x is input data, while w and b represent weight and bias. Weight and bias are generated by random number with value range between 0 and 1 and they will be updated in each hidden layer (Sun, J et al, 2020). Each of input data and activation function in a neuron are multiplied in a hidden layer. This process goes on along the neurons in all hidden layers. In this paper, after several trial and error process, we use a hidden layer with 16 neurons and sigmoid activation function. Besides that, we also use 5000 batch size, it means the sample data used in CNN calculation.

The next step is optimization. In this stage we can calculate the accuracy or the loss function. It represents the similarity between input data and the result or called the error prediction. Adam is popular method for optimization that defined in Equation (3)

$$v_t = (1 - \beta) \sum_{i=1}^t \beta^{t-i} g_i^2 \quad (3)$$

where v is a vector of input data, β represents a constant value (less than 1) while g is the gradient or. Anyway, v will be updated during the iteration (t) (Kingma and Ba, 2017). For loss function we use Mean Squared Error (MSE), it is a general method for calculate the loss function defined in Equation (4).

$$MSE = \frac{1}{n} (Y^* - Y)^2 \quad (4)$$

Y^* and Y are the label of output and input data while n is a total number of data. A good output data is represented by MSE value that tends to zero (Hospodarskyy *et al.*, 2024).

Result and Discussion

We simulate a wave propagation in our geological model with 3 layers that generated using devito (Caunt, 2021), a python package module. A seismic source is placed in the center of our geological model with 100 geophones, (50 geophones in each right and left sides of the source). Then based on this simulation we get our synthetic shot gather model like in Figure 5.

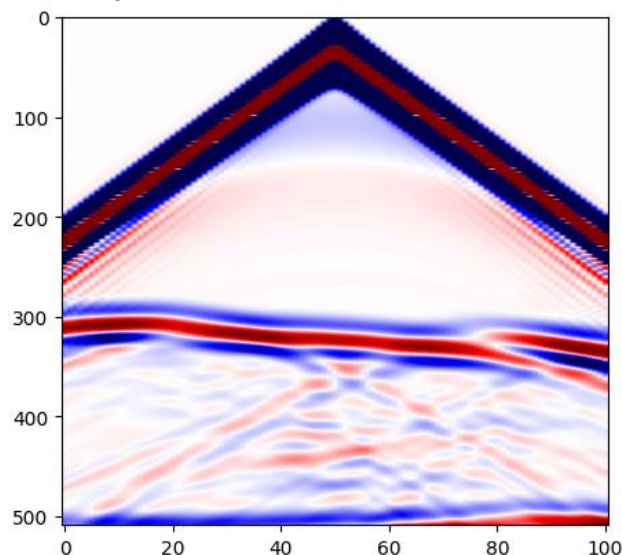


Figure 5. Synthetic shot-gather model

Based on Figure 5, the multiple looks more clearly. Then it will be our input data. For the label, we use the ground truth data by applying butterworth filter with 2nd order and 0.03 frequency value

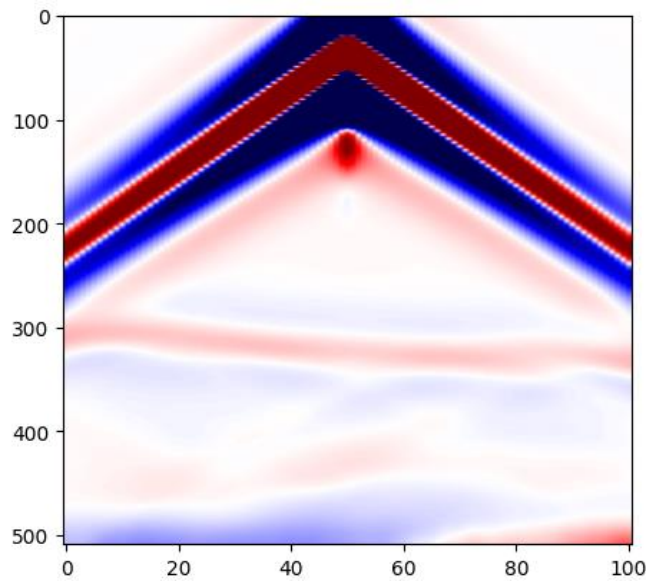


Figure 6. Ground truth synthetic model as the label

In Figure 6, the shot gather is free from the multiple but we also loose information of the boundary layer. This data then processed using CNN with 45 iterations and we get 0.0127 as our final loss function as our best model. The loss function graph can be seen in Figure 7.

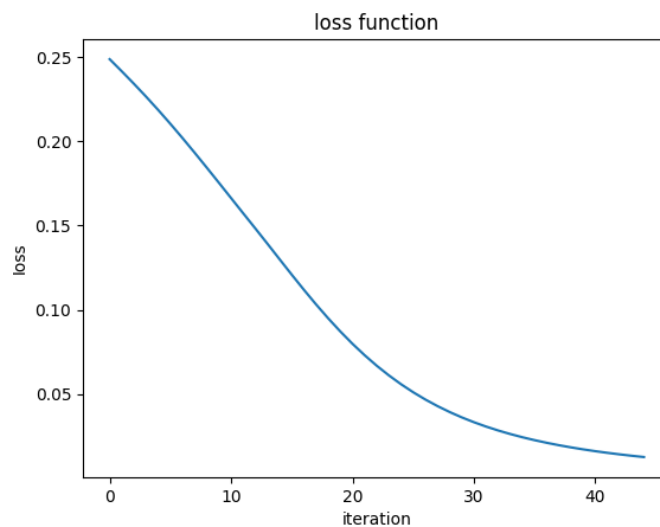


Figure 7. The loss function

Besides loss function, we also calculate Peak Signal to Noise Ratio (PSNR) between removal multiple and the original shot gather for both of the ground truth and CNN. Based on Pandey and Raj (2019), PSNR is defined by Equation (5)

$$PSNR = 10 \log_{10} \left(\frac{\text{squared max possible pixel}}{\text{mean square error}} \right) \quad (5)$$

We get 80.15 and 95.24 for ground truth and CNN model. It means that PSNR of CNN higher than ground truth and proves that CNN is good enough to reinforce the boundaries layer.

CNN works well in removing or attenuating the multiple in our shot gather data and improve shot gather image after butterworth filter. The layer boundaries look more clearly. Besides that, the reflection model also free from the noise. Figure 8 shows the synthetic shot gather, ground truth and shot gather after CNN.

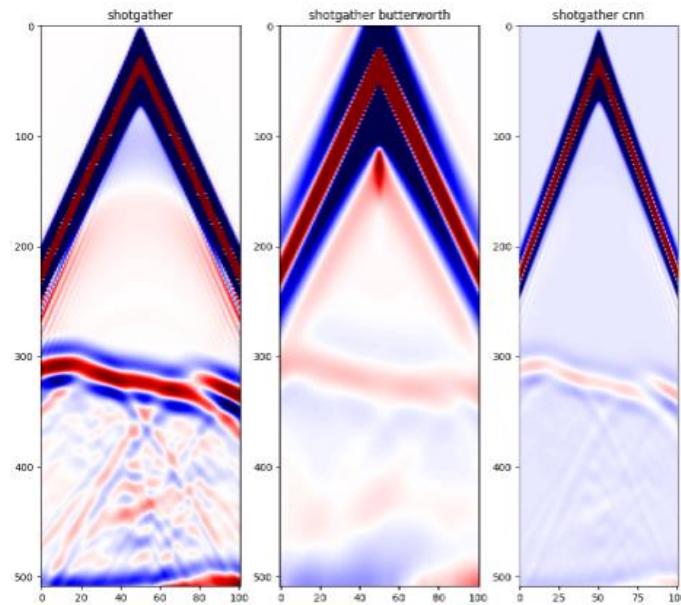


Figure 8. Shot gather, ground truth (butterworth) and shot gather after CNN

According to Figure 8, CNN success in removing the multiple and at the same time, it also improves shot gather model especially in increase seismic image resolution based on shot gather and ground truth data. However, in this study case we use 1- D butterworth filter and 1-D CNN modelling. This way is simpler than applying 2-D FFT and 2-D CNN to shot gather data for resulting the ground truth and improve the shot gather image, although it also can be applied in the same case. Utilities of 2-D FFT and 2-D CNN can be more effective in 3D cube seismic data. It also needs high specification of the computer.

CONCLUSION

Multiple can appear in shot gather or seismic image due to several factors like various layers of geological condition or sea current in marine seismic. It disturbs in seismic interpretation, so it is important to neglect or attenuate multiple from any seismic data. Classical way in removing the multiple is by applying some filters to shot gather or seismic data but sometimes it also eliminates information about the layers. A new method for improving seismic image or shot gather quality is by using Machine Learning method, one example is CNN. CNN works well and very effective in attenuating the multiple and also reinforce boundaries layer that decreasing after the filtering. Furthermore, CNN also can be used to invert the seismic data to Acoustic Impedance data faster than manual inversion method in geophysics.

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