Seismic trace editing by applying machine learning

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Summary

Seismic trace editing is a tedious process in data preprocessing. It may require a great deal of manpower and time cost, especially for a large 3D dataset. In this study, we propose a method based on machine learning to conduct the process automatically. For further improve the feasibility of the scheme, we combine the techniques of Hough transform and Convolutional Neural Network (CNN) for trace editing. The Hough transform is a feature extraction technique which can help to identify anomaly lines in an image, and we apply it to detect possible locations of noisy traces. Then a trained CNN structure is employed to identify the exact noisy traces in the target area. Further automated processing is applied to improve the noisy traces which are selected by the CNN structure, and determine if the processed traces could be useful. Real data tests demonstrate that this approach is promising to perform automated seismic trace editing.

Introduction

Machine learning belongs to the field of computer science, it makes computer systems own the ability of "learning" (i.e., progressively improve the performance on a specific task) using data itself but without any explicit programs (Samuel et al., 1959). In machine learning, the Convolutional Neural Network (CNN) has been successfully employed to detect and classify images (Alex et al., 2012).

Seismic trace editing is a tedious and time-consuming task in seismic data preprocessing. Especially for land data, it may often be interfered by environments, and field operation may encounter various challenges as well, causing partial data in poor quality. Automated editing of seismic traces has been studied extensively in the last a few years

(Chen et al., 1991). McCormack et al. (1993) employ an improved back propagation neural network (BNN) to identify noisy and dead traces in raw field data. Huang et al. (1994) propose a higher-order neural network, called fuzzy function-link net, to identify bad traces. Many statistical methods are also developed to detect bad traces (Stammler, 1993).

In this study, we develop an automated trace editing method by applying the CNN, and the Hough transform methods. CNN structures are designed to be trained with the seismic traces in time and frequency domains. Furthermore, we implement the Hough transform and a band-pass filter to enhance the capability of the scheme. The satisfying results shown in the real data examples demonstrate that the proposed method is promising on trace editing.

Method

CNN is a deep artificial neural network. In this study, we utilize the CNN structures to realize the goal of trace editing.

We design a CNN structure to detect noisy traces in the seismic data. This task can be transformed into an image classification problem; noisy traces are selected to train the CNN structure. After data training, we can apply the trained CNN structure to new seismic data and detect the noisy traces. First, we construct an initial CNN structure which consists of an input and an output layer, as well as multiple hidden layers. Figure 1 displays the CNN structure we designed. The structure contains five kinds of layers: the input layer, convolutional layers, pooling layers, fully connected layers, and the output layer. There are eight layers in total. For the input layer, each seismic trace is transformed into a pixelated image and it should be labeled
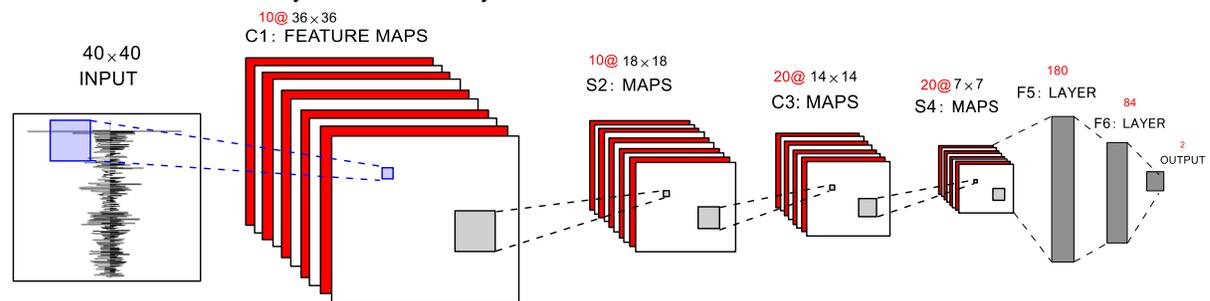

Figure 1: The schematic diagram of the CNN structure we designed to detect the noisy traces.

as good (represented by 1) or noisy (represented by 0) trace as well.

The hidden layers of the designed CNN structure include two convolutional layers, two pooling layers, and two fully connected layers. Convolutional layers apply a convolution operation to the input image, and then passing the result to the next layer. The two convolutional layers contain 10 and 20 convolution filters, respectively. The size of each filter is 5*5 in pixel domain, and they are convolved with the input image at each layer. Then, the max pooling layer is enabled following each convolutional layer to ensure that the dimension of the output is smaller than the input image for decreasing the computational burden in the training stage. Finally, two fully connected layers and the sigmoid function are employed to determine the output value. For example, in this study, it would tell the property of an input trace, i.e., good or noisy trace.

Note that a bias parameter (Chuan et al., 1993) should also be added to each convolutional layer, then the convolution process can be described as the following equation:

$$X_j^L = f\left(\sum_{i \in M_j} X_i^{L-1} * K_{ij}^L + b_j^L\right), \qquad (1)$$

where X^L is the output in layer L, M_j is the gather of input images (X^{L-1}), which are the outputs of layer $L-1$. K is the convolutional filter and b is the bias term. Here, f is the activation function.

Figure 2 shows some samples which are labeled as good (1) or noisy (0) traces, and they are selected from the training dataset.
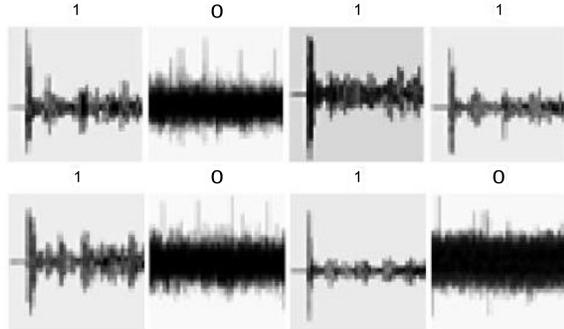
Figure 2: The samples which are labeled as good (1) or noisy (0) traces.

After data training procedure, a trained CNN structure is built, and then we can detect the noisy traces for a new seismic dataset with the trained CNN structure. Note that each input leads to an output value which is the result of the sigmoid function. Therefore, if the output value approximates to 0, the input trace is considered as a noisy

trace. Otherwise, the input trace is a good trace when the output value approximates to 1.

Additionally, for further improve the efficiency of noisy traces detection, we apply the Hough transform to the approach. By doing this, we can use the proposed method to handle the real cases which contain huge number of traces but relatively few noisy ones focused in several areas. With the Hough transform technique, we can capture the primary noisy area first, and then detect the noisy traces in the specific zones but not the whole survey line to save the computational cost. The Hough transform is a feature extraction technique which can help to identify anomaly lines in an image, and it has been widely utilized in image analysis, computer vision, and digital image processing (Shapiro et al., 2001). In the polar coordinate system, the equation of a line is shown below:

$$y = \left(-\frac{\cos \theta}{\sin \theta}\right) * x + \left(\frac{\rho}{\sin \theta}\right). \qquad (2)$$

After we apply Hough transform, the equation shall be converted into the following form:

$$\rho = x * \cos \theta + y * \sin \theta. \qquad (3)$$

Therefore, before applying the CNN structure, we perform the Hough transform with a full seismic gather image, then we choose the areas with $\theta = 0$ which indicate the possible position of the noisy traces, just as the following figures show:
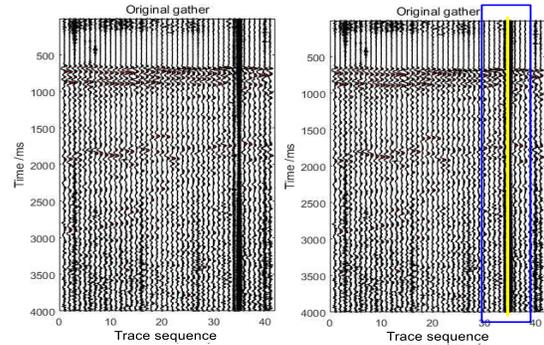

Figure 3: The original gather and the result after Hough transform detection. (The yellow line stands for the possible position where the noisy traces appear.)

Once the possible positions are found, we can design a scanning window (The blue rectangle in Figure 4) for each position; then the CNN structure can be employed in the window to detect the noisy traces, and the computational efficiency would be improved a lot via this strategy. For now, we have focused on the noisy traces by the CNN structure which is combined the Hough transform technique, and this can be the first step of our automated trace editing scheme. However, a second procedure is required for further

Trace editing with CNN and Hough transform

detection because some noisy traces selected by the first step may be good ones after band-pass filtering. Therefore, we develop another CNN structure for the further determination of a trace is truly good or not, and we will call the first step 1st CNN, and the second step we just mentioned above is named 2nd CNN in the following.
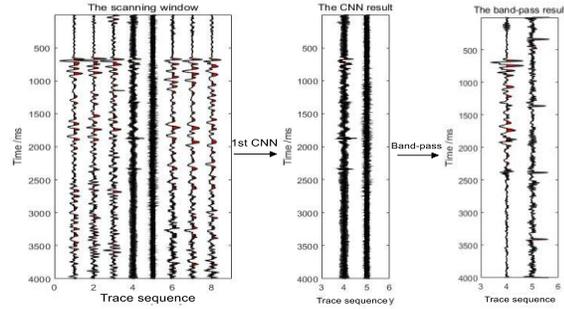

Figure 4: The schematic of the 1st CNN and the band-pass filter.

After the exact noisy traces are detected in the scanning window by the 1st CNN, the band-pass filter is applied to the selected noisy traces; then we calculate the amplitude spectrum of each trace. According to the different appearance in the frequency domain, we can determine whether the noisy traces selected by the 1st CNN structure is truly noise or not. Additionally, by doing this we can fix the useful traces at the same time.

In the 2nd CNN structure, similarly, each noisy trace selected by the 1st CNN should be transformed into an amplitude spectrum image, which is labeled as useful (1) or useless (0) like Figure 5 shows.

In the same manner, we train the 2nd CNN and make it have the ability of detecting the truly noisy traces. Similarly, if the output value approximates to 1, the input trace is considered as a useful trace. Otherwise, the input trace is regarded as a truly noisy trace that should be killed when the output value approximates to 0.
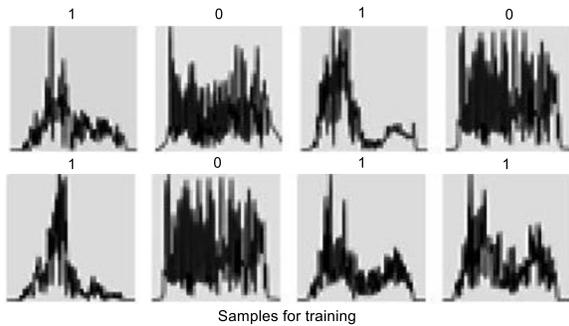

Figure 5: The samples of the 2nd CNN.

Examples

(1) Field example 1

We demonstrate the described method with two field datasets. The first example is shown in Figure 6; we first perform the Hough transform with the original field data image to obtain the scanning windows (The blue rectangles) where the noisy traces may appear. Then the 1st CNN is applied to detect the noisy traces located in the window. The result shows that trace 13, 14, and 17 in the first window are detected as noisy traces. However, these traces may also be useful after further processing. Therefore, we perform the band-pass filter with trace 13, 14, and 17. Then we obtain the amplitude spectrums of the three selected traces. In this example, three traces are all detected as useless through the 2nd CNN, thus, the trace 13, 14, and 17 should be killed after the 2nd CNN. Figure 7 displays the result after the 1st CNN detecting (left) and the final result (right) after performing our automated trace editing method. Note that all the above processes are automated, only the parameters of the band-pass filter are required in advance. Figure 8 shows the whole record and the final result after applying the automated scheme.
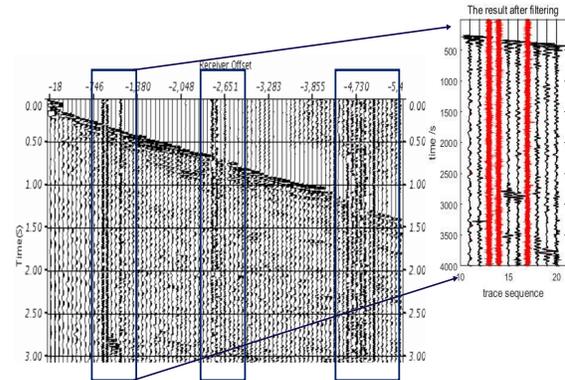

Figure 6: A field data image and the result of the Hough transform scanning (The blue rectangle). Trace 13, 14, and 17 in the scanning window are detected as noisy traces.
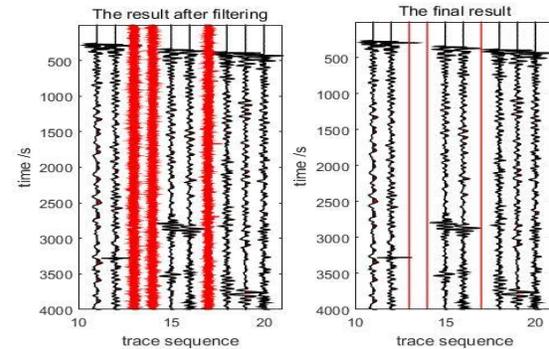

Figure 7: The result after the 1st CNN detecting (left), and the final result (right).

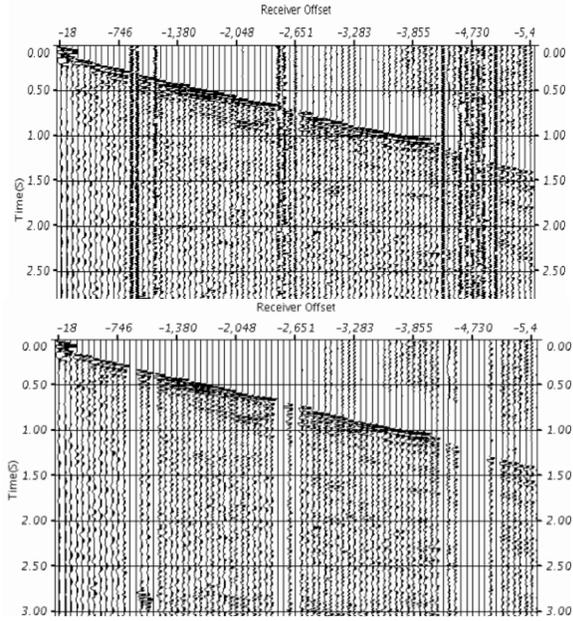# Trace editing with CNN and Hough transform

Figure 8: The raw data (top) and the final result (bottom) after applying the automated trace editing method.

(2) Field example 2

The second field data example is shown in the following figures. In this case, all traces in the last window are detected as noisy traces after the 1st CNN. However, the 2nd CNN result shows that all the seven traces should be reserved after band-pass filtering. Figure 10 displays the raw data and the final result after applying the automated trace editing approach.
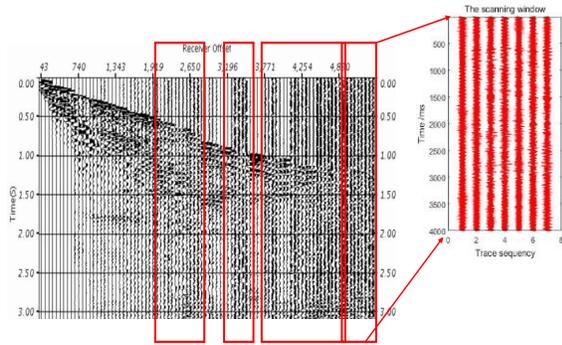

Figure 9: The second field data image and the result of the Hough transform scanning (The red rectangle). Trace 1 to 7 in the scanning window are all detected as noisy traces via the 1st CNN.
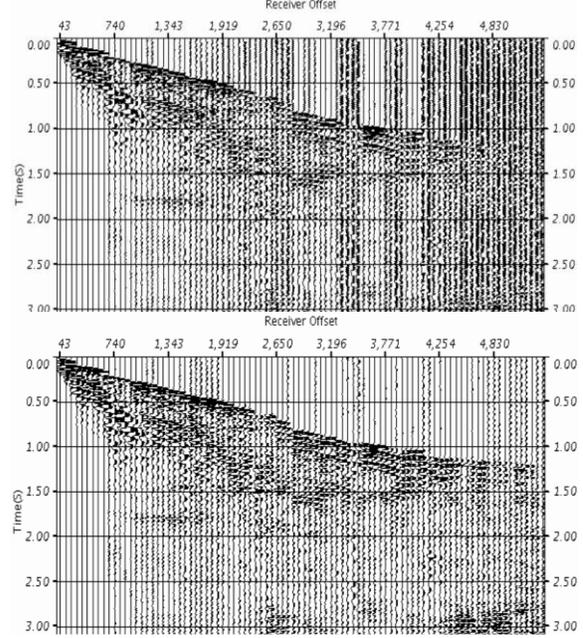

Figure 10: The second raw data (top) and the final result (bottom) after applying the automated trace editing method.

Conclusions

In this study, we combine the Convolutional Neural Network structure with the Hough transform to build an automated trace editing scheme. The efficiency of the CNN-based method is improved with the Hough transform affiliating. Using human-labeled traces as the input, the trained network shows good performance on detecting the noisy and bad traces in real data. Additionally, we can fix the useful traces via the further automated processing at the same time.

One thing we should emphasize that we only focus on the traces with high-frequency noise. There are also some other kinds of noises existing in the seismic data. Therefore, we shall promote this method to detect more types of traces to improve the capability of the trained networks in the future.

Acknowledgments