International Core Journal of Engineering Volume 6 Issue 5, 2020
ISSN: 2414-1895 DOI: 10.6919/ICJE.202005_6(5).0004

Denoising Method of TV-FCN Seismic Data With Bad Track

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Abstract

Total Variation In the process of seismic data collection, missing seismic traces and damage and noise pollution generally occur, which greatly affects the quality of seismic data. In order to solve the shortcomings of traditional shallow methods, a denoising model based on deep learning is proposed. The current seismic data denoising algorithm cannot effectively suppress the noise problem of seismic data with bad tracks. A Total Variation-Fully Convolutional Network (TV-FCN) seismic data bad track reconstruction and denoising method is proposed. The experimental results show that the TV-FCN seismic data bad track reconstruction and denoising method can not only reconstruct the bad tracks efficiently, but also suppress the noise data, and at the same time, the local details of the seismic data can be completely retained without generating artifacts.

Keywords

Seismic data; Deep learning; Denoising.

1. Introduction

In the process of seismic data collection, missing and damaged seismic tracks and noise pollution will greatly affect the quality of seismic data. There are two main methods for reconstructing bad tracks of seismic data: Radon transform based on transform domain, Fourier transform [1 , 2], curved wave transform, etc., based on predictive filtering in the f-x domain bad track reconstruction method [3, 4], but the traditional bad track reconstruction methods are based on certain assumptions and the calculation is more complicated, and these methods are specific in certain cases Talent can have a good bad track reconstruction effect, and its generalization is not strong; traditional denoising needs to be based on the difference between signal and noise characteristics. Common methods are: polynomial fitting method, KL transform method, Curvelet transform, wavelet transform method, etc., polynomial The fitting method has a good denoising effect only after removing the coherent noise; the KL transform method only becomes accurate when the sample is sufficient; the wavelet transform method ignores the characteristics of each pixel and denoises The fuzzy phenomenon will occur at the same time; Curvelet transform overcomes the shortcomings of Fourier transform and wavelet transform, and can maintain the seismic data edge and texture detail information, but it will Degree removes some Curvelet transform coefficients, and denoising will produce artifacts at the same time.

In order to overcome the limitations of traditional shallow denoising models, a non-linear, deep denoising model based on deep learning is proposed. Among them, based on Auto-Encoder (AE) network [5-7], Convolutional Neural Network [8-10] (Convolutional Neural Network, CNN), Generative Adversarial Networks [11-13] (Generative Adversarial Networks, GAN) It is widely used in the field of denoising. In the direction of seismic data denoising, there are fewer denoising methods based on deep learning, and it is mostly used to remove random noise. For example, the random noise removal algorithm based on residual convolutional neural network [14] has strong denoising performance; algorithms using batch normalization, residual learning and hole convolution for denoising of seismic data [15] can be effective To recover edges and fine information; denoising

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model based on convolutional neural network [16], after the model is trained, multiple noises in seismic data cannot be removed simultaneously, and the training time is long, but the above deep learning methods are only applied The random noise is removed, and it is not applied to the denoising of seismic data with bad tracks at the same time.

2. TV-FCN denoising principle

The principle of the bad track reconstruction and denoising method of TV-FCN seismic data, seismic data with bad tracks can be expressed as:

$$Y=S+N+B \tag{1}$$

Among them, Y is seismic data with bad tracks and noise, S is valid seismic data, N is noise, and B is bad track.

This chapter first uses the TV model to solve high-order partial differential equations, and then converts the partial differential equations into numerical difference equations, thereby further obtaining the weighted average formula, and through continuous iteration, the seismic data with bad tracks and noise is repaired for the first time for bad tracks Reconstruction, then on the basis of the TV model bad track reconstruction, the bad track reconstruction is performed again through the FCN network and the noise is suppressed. The FCN network selects the logarithmic hyperbolic cosine loss function to guide the model's convergence direction. Its formula is:

$$L(\theta)=\sum_{i=1}^{n}\log\left(\frac{e^{(S(Y_i;\theta)-S_i)}+e^{-(S(Y_i;\theta)-S_i)}}{2}\right) \tag{2}$$

Where n is the number of training samples, $\theta = \{\omega, b\}$ is the network parameter, ω is the weight, b is paranoid, $S_p(Y_i;\theta)$ is the i-th predicted seismic data without bad tracks and noise, and S_i The i-th real effective seismic data, the smaller the logarithmic hyperbolic cosine error is, the closer $S_p(Y_i;\theta)$ is to S_i, the better the network bad track reconstruction and denoising effect.

The bad track reconstruction and denoising method of TV-FCN seismic data constructed in this paper is based on the TV bad track reconstruction, using Equation 2 and adaptive matrix estimation optimization algorithm, and iteratively optimizes the parameter θ through error back propagation. An optimal network model is obtained, and the seismic data after reconstruction and denoising of the bad track is output.

3. Overall structure of TV-FCN for seismic denoising

3.1 Structural design of residual convolution self-encoding block

Combining the advantages of residual network and convolutional self-encoding network, a residual convolutional self-encoding block (RAE Block) composed of residual block, BN layer and self-encoding structure is proposed. The multilayer RCAE Block structure is shown in Fig.1:

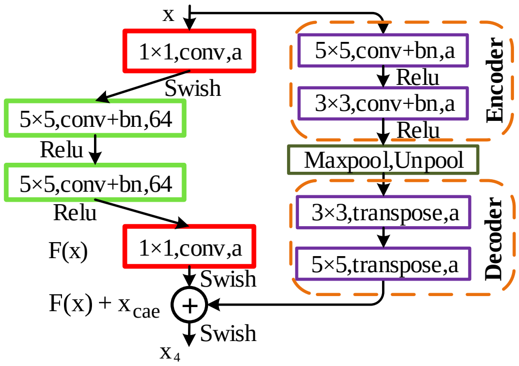

Fig. 1 RAE Block structure

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A represents the number of input and output feature maps; conv is the convolution operation; bn is the batch normalization; the shortcut part is composed of two-layer encoder (Encoder), maximum pooling, de-pooling, and two-layer decoder (Decoder) composition. The main improvement of RAE Block compared to ID Block is: the identity mapping is changed to a convolutional self-encoding structure, and the output is:

$$x_4 = F(x) + x_{cae} \quad (3)$$

Latent features extracted from the encoder by convolution for input x, and the results of 4 convolutional layers for input x.

3.2 TV-FCN overall structure

TV-FCN is a 2 * 8 neural network, which is composed of two 8-layer RAE Blocks;

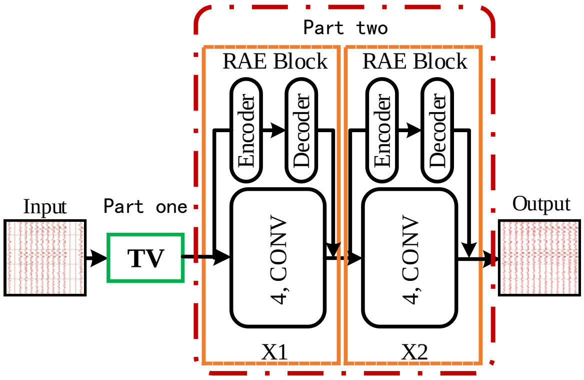

Fig.2 TV-FCN network overall structure

The overall structure of TV-FCN is shown in Figure 5-7. TV-FCN has a total of 32 layers, consisting of input layer, first part, second part, and output layer:

(1) Part one:

TV layer: The single-channel seismic data pre-processed in step 1 is first reconstructed by the TV layer for the bad track. The number of iterations is 20, and the mask is composed of data with a value of 0 in the data containing bad tracks and noise.

(2) Part two:

The second part consists of two 8-layer RAE Blocks.

4. Experimental results and analysis

4.1 Experimental platform

The network models are written based on Tensorflow 10.1. The operating environment CPU is Intel Core i5-8400 and GPU is NVIDIA RTX2080Ti.

4.2 Comparative analysis of experiments

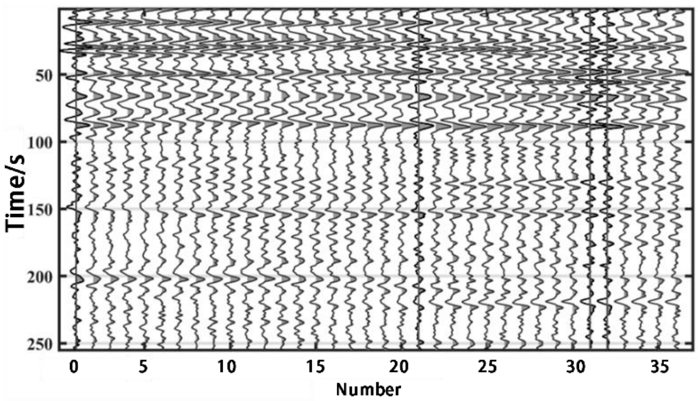

Fig. 3 TV-FCN denoising results

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Fig.3 shows an example of the reconstruction and denoising method of the bad track after the TV-FCN earthquake. Among them, 0, 21, 31, and 32 are the reconstructed bad tracks. It can be seen from the Fig.3 that TV-FCN can not only reconstruct the bad tracks efficiently, but also suppress the noise-reduced data, and at the same time, the local details of the seismic data can be completely retained without generating artifacts.

5. Summary

The TV-FCN method for denoising seismic data with bad tracks is able to maintain clear and coherent trends of the same phase, regardless of whether there are missing single tracks or continuous tracks. And the feasibility of denoising algorithms.

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