Deep nonlinear seismic prior for seismic interpolation
Yuhan Sui∗, Aramco Research Center - Beijing, Xiaojing Wang, Beijing Jiaotong University and Jianwei Ma, Peking University

SUMMARY

Seismic interpolation is an effective technology of reconstructing missing traces to improve the quality of seismic data. Over the past years, the deep learning methods show their powerful performance on seismic interpolation using a convolutional neural network. Recently, an unsupervised deep seismic prior method applies a convolutional neural network to generate the missing traces with one training sample. This method is convenient and suitable for regular and irregular missing seismic data. This method is convenient and suitable for regular and irregular missing seismic data. However, this neural network is based on the linear neurons, which suffer from its limited expressive ability for complex seismic signals. To enhance the capability of high-frequency information using stronger non-linearity neurons, we propose a deep nonlinear seismic prior method for seismic interpolation. Each convolutional layer is replaced by a nonlinear neuron, which is represented by a high-order polynomial of input data and weighted parameters. Numerical experiments illustrate that the proposed method provides better reconstruction results. Moreover, the proposed deep nonlinear seismic prior method learns the useful structure information faster and earlier than the conventional deep seismic prior method.

INTRODUCTION

Due to the physical or financial constraints, the acquisition of seismic data is usually irregularly, which increases the difficulty of seismic data processing. Therefore, seismic interpolation is necessary to improve the accuracy of subsequent seismic data processing. The seismic interpolation can be regarded as an inverse problem, in which the complete seismic data needs to be recovered from the sampled seismic data. According to different assumptions, different kinds of methods have been proposed for seismic data reconstruction. The prediction filter-based methods (Spitz, 1991; Naghizadeh and Sacchi, 2009) assume that the seismic data to be a local linear event in the frequency domain. In the transform-based methods (Sacchi et al., 1998; Yu et al., 2015), seismic data is represented with a linear combination of fixed basis function. And the recovered seismic data is obtained by applying a threshold operator in the transform domain. Rank reduction methods (Ma, 2013; Jia et al., 2016) firstly divide the seismic data into patches, then vectorize these patches and rearrange into a Hankel matrix. It assumes the missing traces will increase the rank of this Hankel matrix.

Recently, the deep learning methods have attracted wide attention and show their powerful performance in seismic data processing (Yu and Ma, 2021). Wang et al. (2019) used the complete seismic data as label and designed the residual networks. The seismic data is reconstructed using the trained network, which achieved more accurate interpolated results. Taking advantage of the good performance of the supervised denoising convolutional neural network (CNN), Zhang et al. (2020) proposed the CNN-POCS method to improve the interpolation accuracy in an iteratively optimized algorithm. To have a good performance, the supervised deep learning methods always need the preparation of training set with high quality as labels. Considering the high requirement of the training samples, many researchers also investigated training the neural network based on the unsupervised mode. Liu et al. (2021) proposed a deep-seismic-prior (DSP) approach to recover irregular and irregular seismic data. An unsupervised Unet network is designed and it captures well the inherent prior of seismic data.

To the best of our knowledge, most of deep neural networks are based on linear neurons, which is represented by a linear combination of the inputs and weights. However, the representation capability of linear neurons is still limited. To further improve the representation capability, the nonlinear neurons (Jiang et al., 2020) are designed, which can be represented by a high-order polynomial of the inputs and its weights. Fan et al. (2018) designed a nonlinear neuron which contains two second-order polynomial terms. Furthermore, Fan et al. (2019) use this nonlinear neuron in auto-encoder neural network for low-dose CT denoising. However, this type neurons may result in the gradient vanishing problem. To make the neural network more stable, Xu et al. (2022) designed a nonlinear neuron which contains a second-order term and a first-order term. Following on this work, we propose an unsupervised deep nonlinear seismic prior (DNSP) for seismic interpolation to improve the representation capability, in which the neurons in DSP are replaced by the nonlinear neurons.

In this work, we first illustrate the theory of nonlinear neuron. Then, we show the architecture of deep neural network. Finally, two synthetic seismic datasets are used to test the validity for seismic interpolation.

THEORY

Most of deep neural network are designed based on the linear neurons, which are the linear combination of inputs and weights, such as convolutional layer. Let X be the input, then the linear neuron is represented as

\[ h(X) = WX + b, \]  

where \( W \) is the weight, and \( b \) is the bias. To further improve the representation capability of deep neural network, one recent progress is the proposal of nonlinear neurons. Different from the linear neuron, the nonlinear neuron can be represented by the high-order polynomial of input \( X \). Here we use the second-order of polynomial to design the nonlinear neuron,
Deep nonlinear seismic prior

\begin{align}
    h'(X) &= B((W_aX + b_1) \otimes (W_bX + b_2)) + (W_cX + b_3), 
\end{align}

which is

\begin{align}
    y &= \sigma(h'(X)) 
\end{align}

Based on equation 2, we generate many nonlinear neurons. Furthermore, we build the architecture of whole deep neural network based on these nonlinear neurons. Given the number of filters in one layer, we first make three conventional convolutional layers. Then we use the Hadamard product to make the second-term of nonlinear neuron. Finally, we replace the linear neurons of deep neural network in DSP by the proposed nonlinear neurons. The Unet is applied in DSP method. Therefore, we replace the convolutional layers of Unet in each block by the nonlinear neurons. All the kernel size is $3 \times 3$. And we use the convolutional layer with stride is 2 instead of the maxpooling layer. The activation function is the LeakyReLU. In the encoder step, the number of filters is $16, 32, 64$ and $128$. And the number of filters in decoder step is $128, 64, 32$ and $16$. Same with DSP, the DNSP is also an unsupervised deep neural network. The input of DNSP is the random number $Z$ with normal distribution. And the loss function is

\begin{align}
    L(\theta) = \| R(f_\theta(Z)) - Y \|_F^2, 
\end{align}

where $f_\theta$ denotes the neural network, $R$ is the sampling matrix and $Y$ is the observed sampled seismic data.

RESULTS

We select two datasets to demonstrate the interpolation performance of the proposed DNSP method. The two datasets (shown in Figure 1(a) and Figure 3(a)) are from the MathGeo2020, an open-source seismic data processing software developed by Center of Geophysics, Harbin Institute of Technology. The time interval of both data is 4ms. The epoch number we set is 5000. And to train the network, we use the Adam optimizer with the learning rate of 0.05. We apply the signal-to-noise ratio (SNR) for quantitative comparison.
Deep nonlinear seismic prior

Figure 3: (a) Complete seismic data. (b) Sampled data with regular missing 50%. (c) Recovered result by DSP. (d) Recovered result by DNSP.

Figure 4: SNR with different epochs.

Figure 5: (a) Sampled data with random missing 60% of data shown in Figure 3(a). (b) Recovered result by DSP. (c) Recovered result by DNSP.
Deep nonlinear seismic prior

Figure 1(a) shows the complete prestack seismic data. We add the Gaussian noise with variance 10 and corrupt data with 25% randomly missing traces, as shown in Figure 1(b). As we can see, around 20th and 150th traces, some events are overlapped. The DSP and proposed DNSP results are shown in Figure 1(c) and Figure 1(d), and the corresponding SNR are 29.77 dB and 30.93 dB. It is clear that the DNSP reconstruction are more continuous and accurate, indicated by the black arrow. Figure 2 shows the SNR curve with different epochs. And the DNSP learns the structure information faster and earlier than DSP. And the nonlinear neurons enhance the representation capability, leading to a higher SNR reconstruction result.

We also test a post stack seismic data which contains a more complex geological structure, as shown in Figure 3(a). The number of traces is 512. We use this data to test the DNSP for regularly missing and randomly missing cases. We first add the Gaussian noise with variance 10 and then corrupt this data with 50% regularly missing traces, as shown in Figure 3(b). The reconstruction results of DSP and DNSP are shown in Figure 3(c) and Figure 3(d), and the computed SNRs are 22.79 dB and 22.90 dB. Both DSP and DNSP reconstruct well. And we also compare the SNR curve with different epochs in Figure 4. It is clear that DNSP learns the useful structure information faster and earlier than DSP. For randomly missing cases, we use the data in Figure 3(a) and add the Gaussian noise with variance 10 and then corrupt this data with 60% randomly missing traces, as shown in Figure 5(a). Figure 5(b) and Figure 5(c) show the DSP and DNSP reconstruction results, respectively. The SNR of DSP and DNSP are 21.08 dB and 21.32 dB. For a detailed comparison, Figure 6(a)-6(d) show the magnified results of Figure 3(a), Figure 5(a), Figure 5(b) and Figure 5(c), respectively. The black arrows indicate that DNSP recovers the sampled data more accurately.

CONCLUSION

We proposed a deep nonlinear seismic prior for seismic interpolation. To enhance the representation capability, the nonlinear neurons, which are represented by high-order polynomials of input data and weighted parameters, are applied in deep neural network. The experimental examples demonstrate that the DNSP outperforms in reconstructing the missing sampled seismic data. Moreover, the DNSP captures the structure information faster and earlier than DSP. In the future work, we will discuss the influence of the learning rate and epoch number, and proposed method will be extend to high-dimensional seismic interpolation.

ACKNOWLEDGMENTS

The authors thank Dr. Tong Zhou for useful suggestions and discussions. This study was supported by the Fundamental Research Funds for the Central Universities No. 2021JBM044, the NSFC under Grant 42204124 and 42230806, China National Petroleum Corporation-Peking University Strategic Cooperation Project of Fundamental Research.