APPLICATION OF DATA AUGMENTATION BASED ON GENERATIVE ADVERSARIAL NETWORK IN IMPEDANCE INVERSION

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ABSTRACT

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In recent years, various deep learning techniques have been widely used in the field of geophysics. As far as seismic impedance inversion is concerned, a nonlinear mapping model from seismic data to wave impedance can be established by training the depth inversion network, and then the impedance information can be predicted by the nonlinear model. However, the effectiveness of the current impedance inversion methods based on deep neural networks depends on the number of labels. The generalization ability of the model trained in the state of few labels is poor. Data augmentation can alleviate this situation by using the existing data. Therefore, the author proposes a method based on generative adversarial network (GAN) to augment the labels in the original data set, and uses geophysical forward modeling technology to forward seismic data to achieve the function of data augmentation. Unlike existing GAN, which generates samples directly from noise, the method augments the labeled data from the original dataset. The validity of this method is verified by model data and actual data. The method provides a data augmentation seismic inversion technique based on GAN for impedance inversion.

KEY WORDS: impedance inversion, temporal convolutional network, data augmentation, generative adversarial network.

INTRODUCTION

Deep learning is to learn the internal rules and representation levels of samples. It is widely used in computer image processing and natural language processing and has achieved great success (Razzak et al., 2018; Wang et al., 2020). The key to its success lies in the large amount of data.

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However, there are relatively few data sets available for learning, so the generalization ability of the model obtained by training deep network on small data sets is often poor in the test set. To solve the above problems, the general solution is to add "dropout" layer (Hinton et al., 2012), batch normalization (Ioffe and Szegedy, 2015), layer normalization (Ba et al., 2016), weight normalization (Salimans and Kingma, 2016) etc., in the network layer, but the ability of these methods to solve the problem is very limited (Antoniou et al., 2017). The most direct and effective solution is to add more high-quality data to the training dataset. However, manually adding additional high-quality data is expensive and time-consuming, which is sometimes impossible for data under complex conditions. At present, a relatively wide range of solutions is to augment the original dataset. In terms of computer image processing, data augmentation is mainly achieved through geometric transformation, color transformation, random erasing, feature space enhancement etc. (Shorten and Khoshgoftaar, 2019; Mikołajczyk and Grochowski, 2018). In terms of natural language processing, such as vocabulary substitution, back translation, noise injection, etc. (Bayer et al., 2022; Feng et al., 2021). In recent years, GAN is widely used in computer image processing and natural language processing. For example, Suh et al. proposed to solve the problem of data imbalance based on GAN (Suh et al., 2019), Pascual et al. proposed language enhancement methods based on GAN (Pascual et al., 2017), and these methods all generated new data based on GAN.

In terms of supervised learning impedance inversion, it is not enough to train a model with good generalization ability with a small number of labeled data. In order to make up for the lack of labeled data, Yi et al. implemented impedance inversion by data augmentation and active learning (Yi et al., 2021). Cai et al. (2020) proposed an impedance inversion method based on GAN to further improve the generalization ability of the inversion model. On the basis of previous work, this paper proposes a data augmentation method based on GAN to construct impedance inversion model.

Aiming at the stability of GAN training, the author used Wasserstein GAN with gradient penalty (WGAN-GP) proposed by Gulrajani et al. (2017), and used the temporal convolutional network (TCN) with the characteristics of convolutional neural network (CNN) and recurrent neural network (RNN) to build the inversion generator and forward generator in GAN. At the same time, through the seismic forward modeling technique in geophysics, the author convolved the wavelet with the impedance generated in the adversarial network to obtain the synthetic record. Finally, the synthetic record and the generated impedance are added to the original data set to achieve the purpose of data augmentation. The validity of the method is verified by the test of model data and real seismic data.

DATA AUGMENTATION BASED ON GAN

Generative adversarial network is a new framework proposed by Goodfellow et al. (Goodfellow et al., 2014). Its applications in image processing mainly include image composite, image transformation, image super-resolution, etc. (Ledig et al., 2017; Nie et al., 2017). Applications in NLP mainly include machine translation, discourse analysis, etc. (Du and Huang, 2019; Young et al., 2018). GAN mainly consists of two adversarial neural networks, which are respectively used as generator G and discriminator D, where G is used to generate new data and D is used to distinguish real data from generated data. According to the idea of seismic forward and inversion, Wang et al. used GAN to realize impedance inversion (Wang et al., 2022).

The author uses TCN to construct generators. The generators built based on TCN include inversion generator G_B and forward generator G_F. The main architecture consists of fully convolutional network, dilated convolution, causal convolution and residual block (Bai et al., 2018), whose network structure is shown in Fig. 1. The purpose of the inversion generator G_B is to learn the nonlinear mapping of seismic data to impedance, and the purpose of the forward generator G_F is to learn the nonlinear mapping of impedance to seismic data. Through the seismic forward modeling technique in geophysics, the author convolved the wavelet with the impedance generated in the adversarial network to obtain the synthetic record. The discriminators include seismic discriminator D_S and impedance discriminator D_{AI}, both of which are built by multilayer perceptron (MLP). The purpose of the seismic data discriminator D_S is to distinguish between real and generated seismic data, and the purpose of the impedance discriminator D_{AI} is to distinguish between real and generated impedance data. Through the above methods, the author constructs a data augmentation method based on GAN and applies it in impedance inversion.

CONSTRUCTION OF SEISMIC IMPEDANCE INVERSION MAPPING MODEL

The construction of impedance inversion mapping model is the key of supervised learning inversion method, which mainly involves two parts: dataset and deep learning network.

Data augmentation method

The working mechanism of impedance inversion method based on data augmentation of GAN is as follows:

Step 1: preprocessing of sample data. It mainly includes the following processing methods: dataset division, the author divided the whole sample set $N_t\{x_t, y_t\}$ into labeled dataset $N_l\{x_l, y_l\}$, unlabeled dataset $N_u\{x_u, y_u\}$ and test dataset $N_{val}\{x_{val}, y_{val}\}$, where x is seismic data, y is impedance; Next is to normalize the data, random assignment etc.. The formula of data normalization method used in this paper is as follows:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad . \tag{1}$$

In eq. (1), x is the original data, x_{max} and x_{min} are the maximum and minimum values of the original dataset respectively.

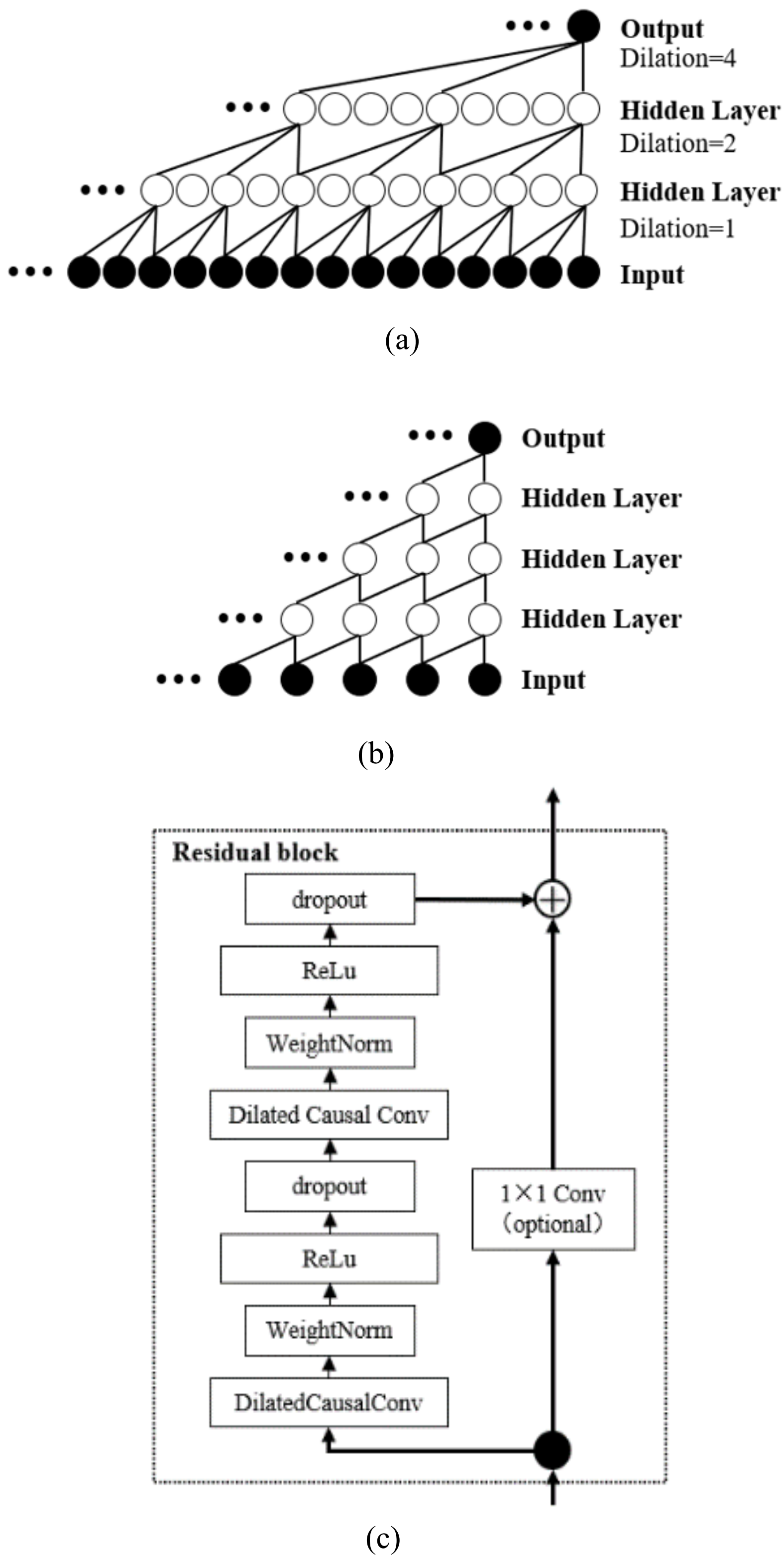


Fig. 1. Structure of generator. Dilated convolution (a), causal convolution (b), residual block (c).

Step 2: pre-train the generators. Before adversarial training, the labeled dataset is used to pre-train the inversion generator G_B and forward generator G_F respectively. In the pre-training stage, the target loss function of the inversion generator G_B and the forward generator is the Mean Square Error (MSE):

$$Loss = \frac{1}{n}\sum(y_i - \hat{y}_i)^2 \quad , \tag{2}$$

where n is the number of samples, for G_B, y_i is the predicted impedance $\hat{y}_i$ is the true impedance; for G_F, y_i is the predicted seismic data, $\hat{y}_i$ is the real seismic data.

Step 3: build GAN. The architecture of GAN is shown in Fig. 2. The loss function of the seismic data discriminator D_S is:

$$L_{D_S} = L_{S_l} + L_{S_u} \quad , \tag{3}$$

$$L_{S_l} = \underbrace{\left[E_{x_l \in T_l}\left[D_S\left(G_F(y_l)\right)\right] - E_{y_l \in T_l}\left[D_S(x_l)\right]\right]}_{\text{Adversarial loss of labeled seismic data}} + \underbrace{\lambda_1 E\left[\left(\left\|\nabla_{\hat{S}} D(\hat{S})\right\|_2 - 1\right)^2\right]}_{\text{Gradient penalty}} \quad , \tag{4}$$

$$L_{S_u} = \underbrace{\left[E_{x_u \in T_u}\left[D_S\left(G_F(G_B(x_u))\right)\right] - E_{x_u \in T_u}\left[D_S(x_u)\right]\right]}_{\text{Adversarial loss of unlabeled seismic data}} + \underbrace{\lambda_2 E[(\|\nabla_{\widehat{S^*}} D(\widehat{S^*})\|_2 - 1)^2]}_{\text{Gradient penalty}} \quad . \tag{5}$$

In eq. (4), $G_F(y_l)$ represents the seismic data generated by the forward generator through the true labels, and $\hat{S}$ represents the linear interpolation between$G_F(y_l)$ and x_l:

$$\hat{y} = \alpha x_l + (1-\alpha)G_F(y_l), \alpha \in [0,1] \quad . \tag{6}$$

In eq. (5), $G_B(x_u)$ represents the impedance data generated by the inversion generator through unlabeled seismic data, and $\widehat{S^*}$ represents the linear interpolation between $G_F(G_B(x_u)$ and x_u .The loss function of the impedance discriminator D_{AI} is:

$$L_{D_{AI}} =$$

$$\underbrace{\left[E_{x_l \in T_l}\left[D_{AI}\left(G_B(x_l)\right)\right] - E_{y_l \in T_l}\left[D_{AI}(y_l)\right]\right]}_{\text{Adversarial loss of impedance}} + \underbrace{\lambda_3 E\left[\left(\left\|\nabla_{\widehat{AI}} D(\widehat{AI})\right\|_2 - 1\right)^2\right]}_{\text{Gradient penalty}} \tag{7}$$

where $G_B(x_l)$ is the impedance data generated by the inversion generator from the annotated seismic data, $\widehat{AI}$ is the linear interpolation between $G_B(x_l)$ and y_l.The purpose of the inversion generator G_B is to generate impedance, and its loss function is as follows:

$$L_{G_B} = \underbrace{\gamma_1[MSE(G_B(x_l), y_l)]}_{\text{Loss of impedance}} + \underbrace{\left[E_{x_l \in T_l}[D_{AI}(G_B(x_l))] - E_{y_l \in T_l}[D_{AI}(y_l)]\right]}_{\text{Adversarial loss of impedance}} +$$

$$\underbrace{\gamma_2\left[MSE\left(G_F\left(G_B(x_{l+u})\right), x_{l+u}\right)\right]}_{\text{loss of seismic data}} +$$

$$\underbrace{E_{x_{l+u} \in T_l + T_u}\left[D_S\left(G_F\left(G_B(x_{l+u})\right)\right)\right] - E_{x_{l+u} \in T_l + T_u}[D_S(x_{l+u})]}_{\text{Adversarial loss of seismic data}} \quad . \tag{8}$$

The loss function of the forward generator G_F is:

$$L_{G_F} =$$

$$\underbrace{\gamma_2\left[MSE\left(G_F\left(G_B(x_{l+u})\right), x_{l+u}\right)\right]}_{\text{loss of seismic data}} +$$

$$\underbrace{E_{x_{l+u} \in T_l + T_u}\left[D_S\left(G_F\left(G_B(x_{l+u})\right)\right)\right] - E_{x_{l+u} \in T_l + T_u}[D_S(x_{l+u})]}_{\text{Adversarial loss of seismic data}} \quad . \tag{9}$$

Step 4: geophysical forward modeling. Through the seismic forward modeling technique in geophysics, the author convolved the wavelet with the impedance generated in the adversarial network to obtain the synthetic record. The synthetic record and the generated impedance are added to the original dataset to achieve the purpose of data augmentation.

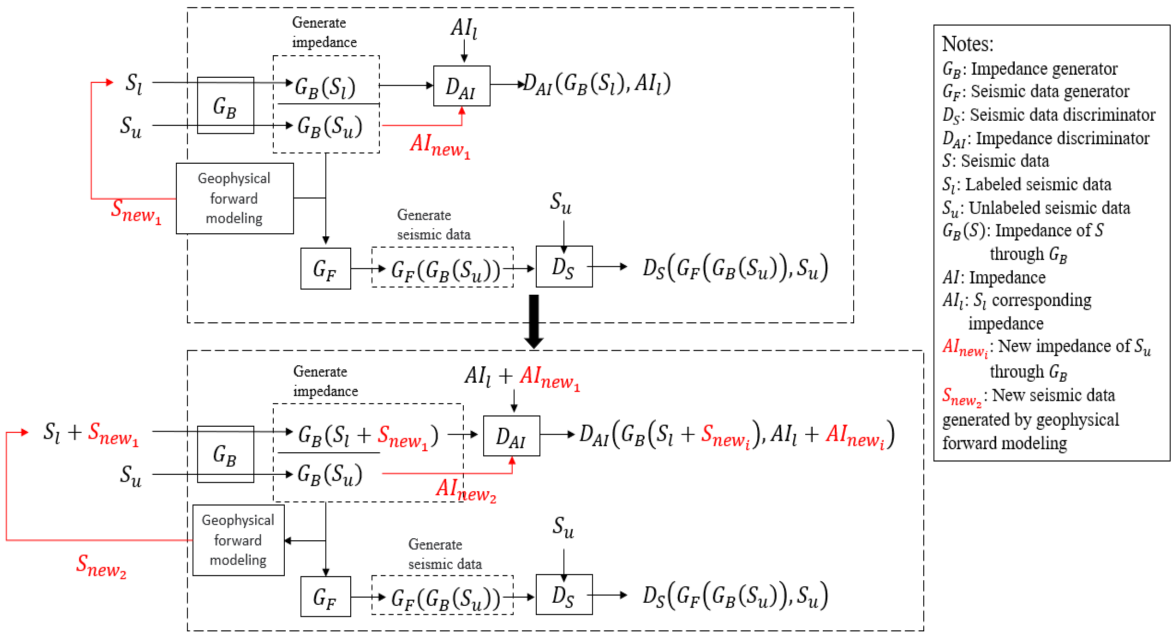
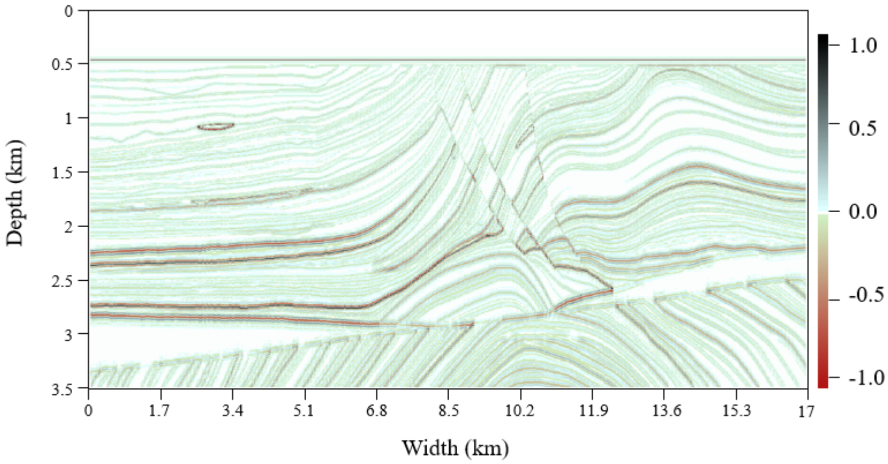


Fig. 2. The architecture of GAN.

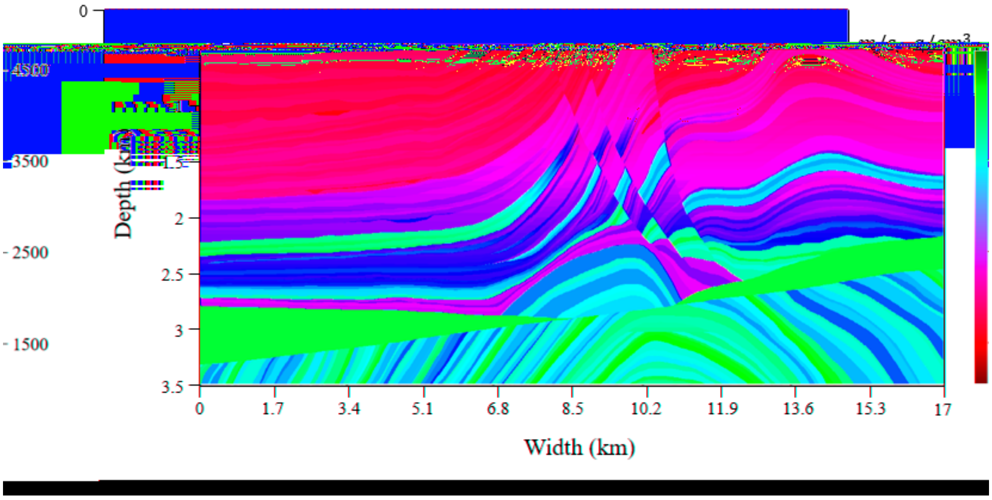
Finally: select the best model for prediction. The standard is mainly based on the loss change curve and the inversion fitting curve of the test set to determine whether hyperparameters such as training times, batch sample number and learning rate need to be adjusted. Finally, all seismic data are input into the optimal inversion generator G_B to obtain the final predicted impedance inversion result.

MARMOUSI-2 MODEL

In order to verify the feasibility of the proposed method, the author uses open dataset Marmousi-2 model for testing. The model is an update and upgrade of the original Marmousi model, and has been applied to a large number of geophysical studies, including seismic inversion, seismic migration and multi-component imaging, etc. Fig. 3(a) and Fig. 3(b) show the Marmousi-2 seismic profile and corresponding impedance profile, respectively. The model has a width of 17 km and a depth of 3.5 km. There are 2721 seismic traces and corresponding impedance data, and the number of samples in each trace is 701.



(a)



(b)

Fig. 3. Model data. Marmousi-2 seismic profile (a), Marmousi-2 impedance profile (b).

The author divided the dataset of the model, as shown in Fig. 4. In the total dataset $N_t\{x_t, y_t\}$, 300 traces are randomly selected as labeled dataset $N_l\{x_l, y_l\}$, and then 300 traces are randomly selected as unlabeled dataset $N_u\{x_u, y_u\}$, in which dataset $N_l\{x_l, y_l\}$ and $N_u\{x_u, y_u\}$ do not overlap. Finally, the remaining data is used as a test set $N_{val}\{x_{val}, y_{val}\}$ to evaluate the generalization ability of the proposed model.

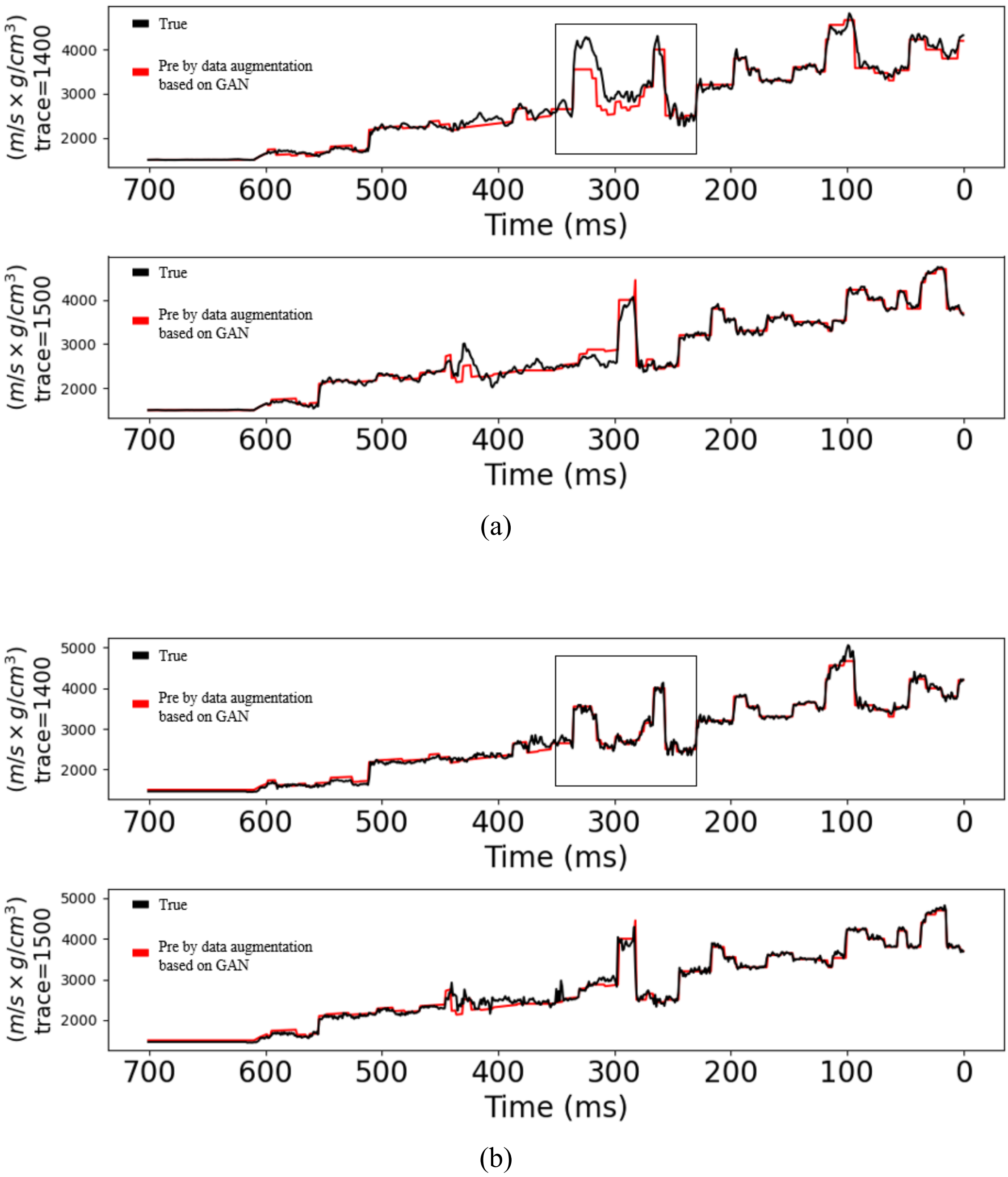
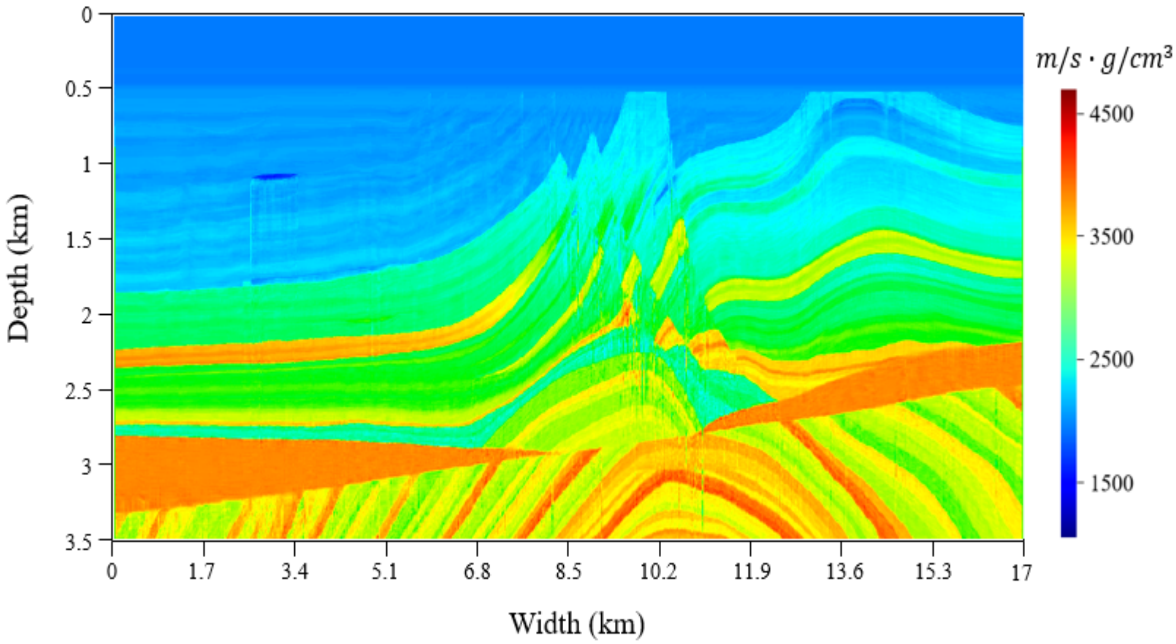
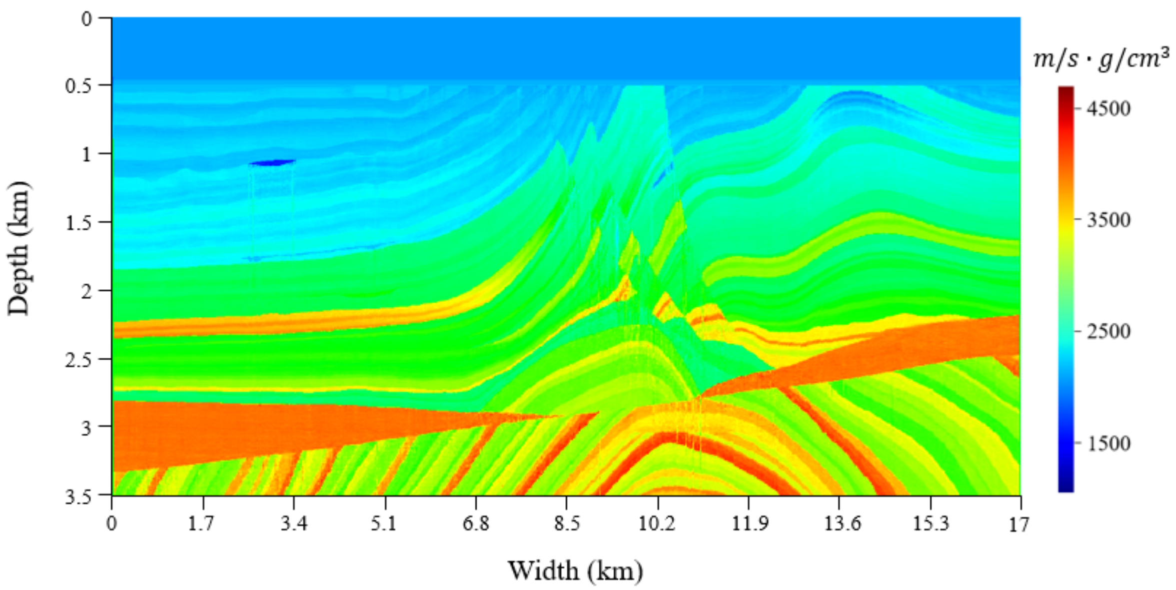


Fig. 4. (a) Comparison of single trace fitting TCN. (b) Data augmentation based on GAN.

The inversion generator G_B and forward generator G_F are pre-trained on the labeled dataset, and then the labeled dataset and the unlabeled dataset are used for adversarial training. The results obtained after 2000 epochs training are compared with the TCN method. The inversion results are shown in Figs. 4, 5 and 6. Fig. 4 shows the comparison of single-trace fitting between impedance and predicted impedance. By observing the selected area in the frame in Fig. 4, it can be found that the single-trace fitting result obtained by the method of data augmentation is better. Fig. 5 shows the inversion profile comparison, and Fig. 6 shows the inversion difference profile comparison. By observing Figs. 5 and 6, it can be found that the inversion results by means of data augmentation are clearer.

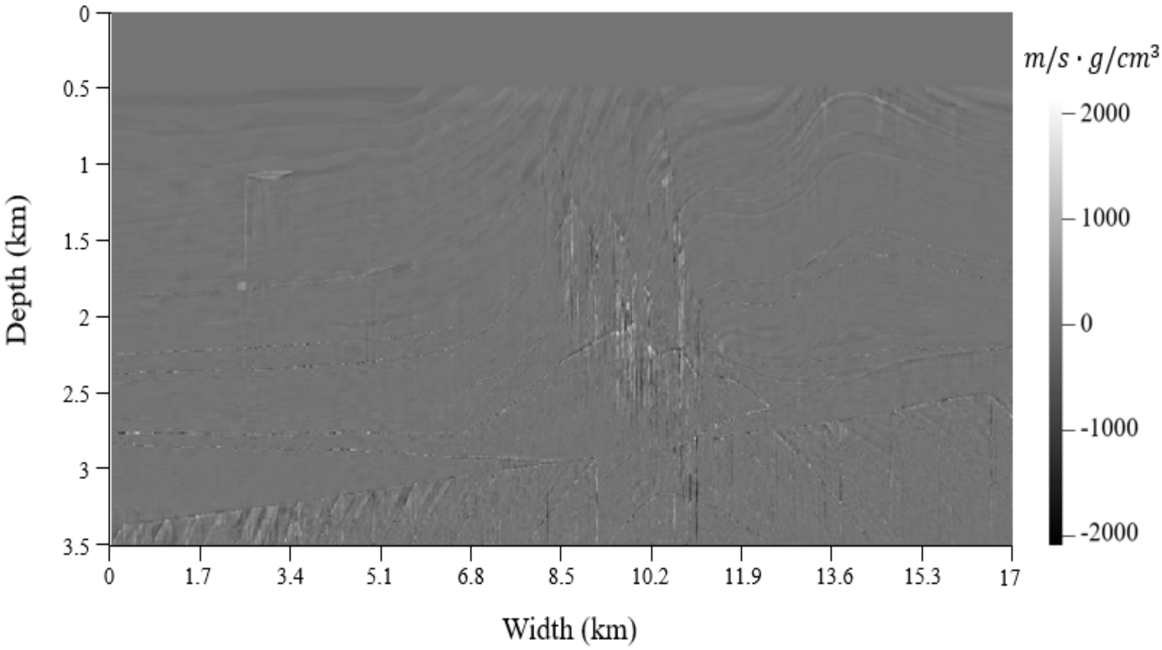


(a)

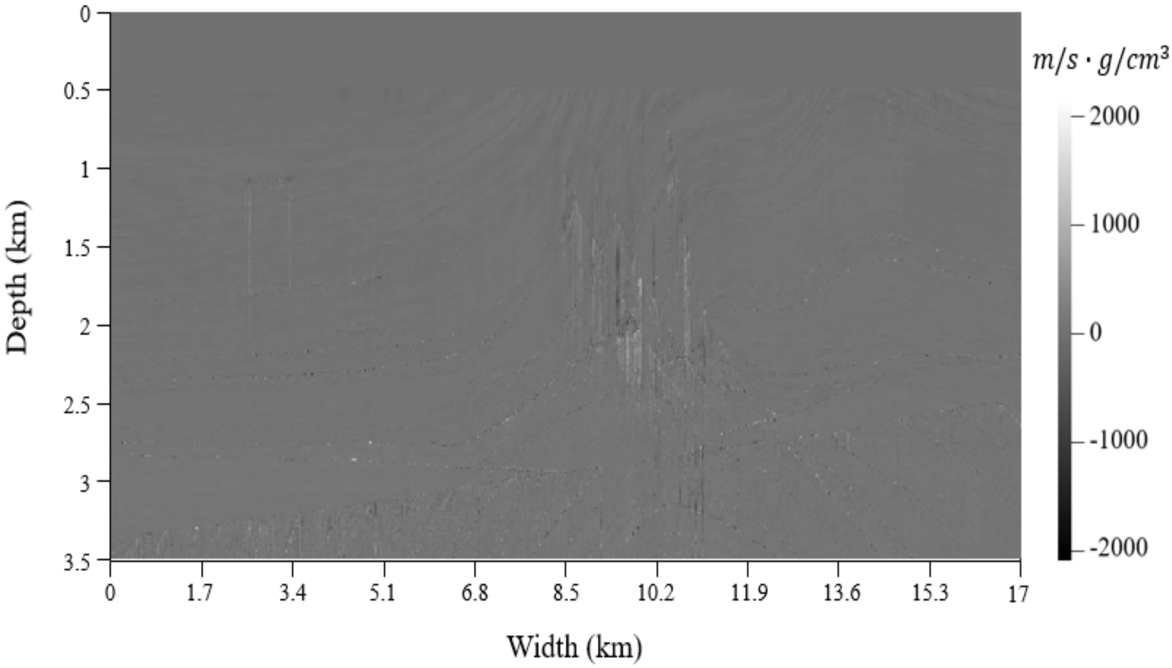


(b)

Fig. 5. (a) Comparison of impedance profiles TCN. (b) Data augmentation based on GAN.



(a)



(b)

Fig. 6. (a) Comparison of impedance profile difference. TCN. (b) Data augmentation based on GAN.

The author introduced Pearson Correlation Coefficient (PCC) and Coefficient of Determination (r^2) for quantitative analysis, and the results are shown in Table 1. Through the above comparison, it can be concluded that the inversion results obtained by the augmented method based on GAN have higher accuracy.

Table 1. Comparison of experimental results and parameters between the two methods.

Evaluation / Methods	train set PCC /%	train set r^2 /%	test set PCC /%	test set r^2 /%
TCN	99.53	99.15	98.49	98.99
Method of the paper	99.73	99.54	99.67	99.34

THE PRACTICAL APPLICATION

In order to further prove the effectiveness of the method, the author uses the actual data to test. There are 40 inlines and 110 crosslines in the 3D data volume of a working area, the number of sample points in each trace is 254, and the sample point interval is 1 ms. The main lithology of this area is sandstone and mudstone. There are 15 Wells containing acoustic and density logging data. The partial profile of seismic data is shown in Fig. 7 the 3D data volume has a total of 4400 traces, from which 400 traces are selected as the labeled data set and 400 traces are selected as the unlabeled data set. The labeled data set contains 5 Wells. After preprocessing the data, it is put into the proposed adversarial inversion network to obtain the inversion results, as shown in Fig. 11. By comparing Fig. 10 (results predicted by TCN) and Fig. 11, it can be seen that the impedance obtained by the proposed method is in good agreement with the logging interpretation.

The example proves that the impedance inversion method based on GAN data augmentation can get better inversion results, and the method can be applied in sand and mudstone prediction, which provides a new technical means for seismic reservoir prediction.

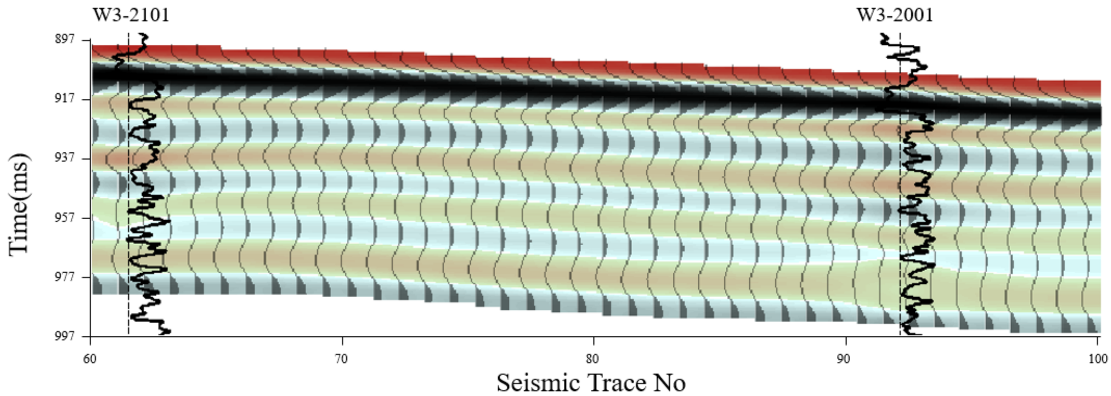


Fig. 7. Partial section of actual seismic data in the working area.

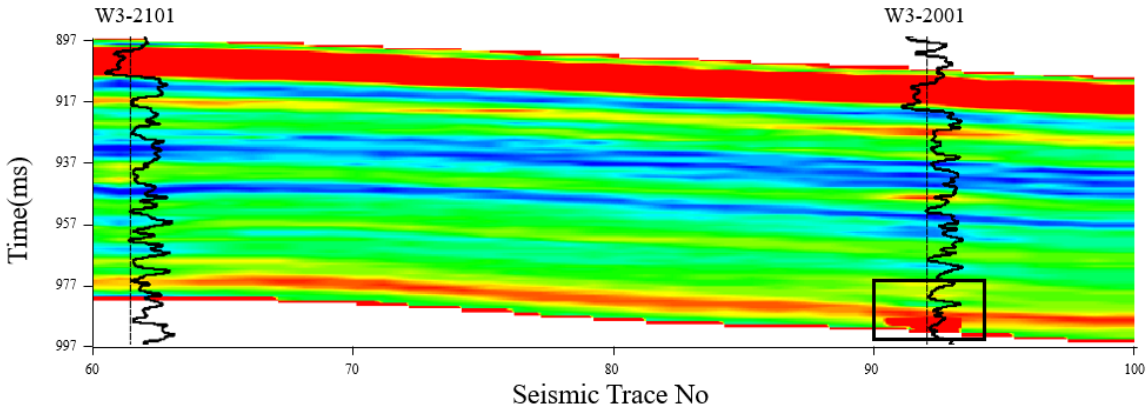


Fig. 8. TCN.

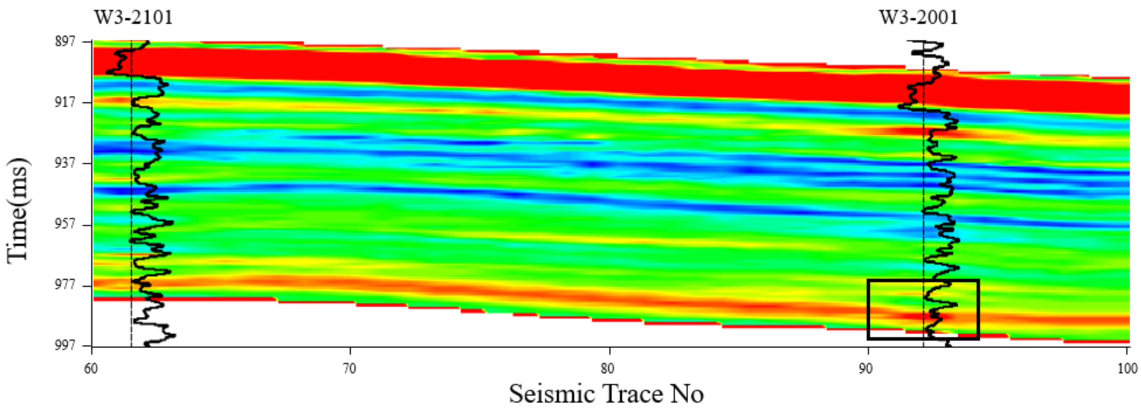


Fig. 9. Data augmentation based on GAN.

CONCLUSION

In this paper, a data augmentation method based on generative adversarial network is proposed. Unlike the existing GAN method, which directly generates samples from noise, this method augments the original dataset to improve the quality of generated data, and the method is applied to impedance inversion. Under the condition of few labels, the model trained by the proposed method still has good generalization ability, and the inversion result is better than that of the non-augmented method. Next, it is worth exploring whether the method can be applied to other potential scenarios in geophysics.

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