Introduction

Post-stack (or migrated) seismic data can be modeled as the convolution of seismic wavelet with reflectivity according to the convolutional model (Robinson, 1985). It is well-known that seismic wavelet is band-limited, which leads to the resolution of seismic data is inevitable to be reduced during convolution, and further results in the inverse problem that estimates reflectivity from seismic data being nonlinear and ill-posed (Chen et al, 2019). There are many methods to enhance the resolution of seismic data, such as spectrum whitening (SW) (Sajid, 2014), inverse Q filtering (Morozov, 2018), etc.

As a deep learning technique, Generative Adversarial Networks (GANs) was proposed by Goodfellow et al. (2014). GANs consists of a generator and a discriminator, the discriminator will make the generator to output better images in an adversarial mechanism. Many popular and powerful frame works are developed based on GANs in recent years. Conditional GANs, which was proposed by Mirza et al (2014), incorporate the classification label to generate specific category images. The stability of training GANs is another important research topic. Arjovsky et al (2017) proposed to replace Kullback-Leibler (KL) divergence with Wasserstein distance.

In this paper, we will investigate the application of GANs in seismic deconvolution by proposing a new GAN called Reflectivity-GAN. We use Reflectivity-GAN to generate seismic reflectivity from seismic data with assuming the wavelet is known. To improve the robustness of the generator of Reflectivity-GAN, we utilize the Wasserstein loss with gradient penalty (Gulrajani et al, 2017) in our loss function, which results in the network training becoming stable and converging fast. We use synthetic and field data examples to assess the performance of the proposed method, and the results clearly demonstrate the advantages of the proposed method in generating high-quality reflectivity over other physics-driven common methods.

The conventional method

According to the convolutional model, the seismic trace $s(t)$ can be considered as a convolution of the seismic wavelet and reflectivity, which can be presented as:

$$s(t) = w(t) * r(t) + n(t)$$  \hspace{1cm} (1)

where $r(t)$ is reflectivity, $w(t)$ is seismic wavelet and $n(t)$ represent the additive noise. The objective of seismic high resolution inversion is to solve for an optimal reflectivity of $r(t)$, which is often realized through an optimization problem that least squares with an L1 regularizer denoted as:

$$\hat{r} = \min \frac{1}{2} \left\| s(t) - w(t) * \hat{r}(t) \right\|_2^2 + \lambda \left\| \hat{r}(t) \right\|_1$$  \hspace{1cm} (2)

where $\lambda$ is a nonnegative regularization parameter, $\hat{r}(t)$ is estimated reflectivity. The wavelet $w(t)$ is the same as what we use for the Reflectivity-GAN, and the L1-norm regularizer can enhance the sparsity of solution.

Generator

Affected by the phase of the wavelet, when we directly use seismic data as the input of the network, some incorrect reflectivity may be generated. To avoid this, we use an initial reflectivity produced by the least squares method from seismic data and wavelet as the input. The whole input data collection is a tensor with a dimension of $N_s \times 1 \times 3$, where the first dimension is the length of seismic data, the second dimension denotes the number of traces and the third dimension denotes the channels of the input. The input 2 channels are the initial reflectivity, seismic wavelet and seismic trace. As illustrated in Figure 1, the deep generator network contains 7 identical blocks and each block has three convolutional layers as shown in the “A block” in Figure 1. Consequently, the generator has a total of 21 convolutional layers. Inside each block, the first and second convolutional layers is followed by batch-normalization (BN) layers and rectified linear unit (ReLU). For the third convolutional layers,
only the last two feature maps will be ReLUed and they will be used to replace the last two channels of input data. Besides, the first feature map will be added into the first channel of input data. Inside each block, the first two convolutional layers have the kernel size of $3 \times 1$ with stride is 1 and the number of feature maps is 32, the third convolutional layers have the same kernel size but the number of feature maps is changed to 3. The input and output data of each block have the same dimension of $N_s \times 1 \times 3$, and the first feature map of the output data corresponding to the last block is the inversion result.

**Figure 1** An illustration of Generator Network.

**Discriminator**

We train a discriminator network to discriminate real reflectivity from generated reflectivity. Similar to the VGG network (Simonyan and Zisserman, 2014), the structure of the discriminator is shown in Figure 2. We use the LeakyReLU activation function and the strided convolution (stride=2) instead of max-pooling throughout the network. When the strided convolutions are used to reduce the resolution each time, the number of features is doubled (from 64 to 512) to reduce the loss of useful information. The resulting 512 feature maps will be reshaped and connect with a fully connected (FC) layer. Because of the Wasserstein loss function is used in training, we don't need a sigmoid activation function to obtain a probability for sample classification in the final layer.

**Figure 2** An illustration of Generator Network with corresponding number of feature maps (n) and stride (s) indicated for each convolutional layer.

**Loss function**

Wasserstein GAN (WGAN) with gradient penalty has been proved to be effective in improving the robustness of variety of generator architectures. We use Wasserstein loss with gradient penalty as our loss function to distinguish the real reflectivity and the generated reflectivity. The loss function of discriminator is defined as:

$$L_d = \mathbb{E}_{\tilde{r} \sim \mathbb{P}_{\text{gen}}} D(\tilde{r}) - \mathbb{E}_{r \sim \mathbb{P}_{\text{real}}} D(r) + \alpha \mathbb{E}_{\tilde{r} \sim \mathbb{P}_{\text{gen}}} \left(\|\nabla_{\tilde{r}} D(\tilde{r})\|_2 \right)^2$$

where $\alpha$ is a nonnegative parameter, $\mathbb{P}_{\text{gen}}$ means the generated reflectivity distribution, $\mathbb{P}_{\text{real}}$ is the real reflectivity distribution, and $\mathbb{P}_r$ is random samples from both $\mathbb{P}_{\text{gen}}$ and $\mathbb{P}_{\text{real}}$. 
For the generator, we want the generated reflectivity can not only fool the discriminator but also reveal the true reflectivity. Therefore, the loss function is a combination of the adversarial loss and content loss:

\[
L_{g\text{-adv}} = - \mathbb{E}_{\tilde{r} \sim \mathcal{G}_{\text{gen}}} D(\tilde{r})
\]

\[
L_{g\text{-con}} = \beta_1 \|\tilde{r} - r\|_1 + \beta_2 \|\tilde{r} - r\|_2^2
\]

where \(\beta_1\) and \(\beta_2\) are nonnegative parameter, \(r\) is reflectivity obtained by generator. Therefore, the loss function of generator is formulated as:

\[
L_g = - \mathbb{E}_{\tilde{r} \sim \mathcal{G}_{\text{gen}}} D(\tilde{r}) + \beta_1 \|\tilde{r} - r\|_1 + \beta_2 \|\tilde{r} - r\|_2^2
\]

**Examples**

The Ricker wavelet with peak frequency is 30 Hz is used in this test and we use the reflectivity models of the validation set to test reflectivity inversion. In order to highlight the effectiveness of the proposed method, we also estimate reflectivity models by solving equation (2) using the Fast Iterative Soft-Thresholding Algorithm (FISTA) method. The implementation of FISTA is based on the open-source optimization toolbox SPAMS.

![Figure 3 Comparison of using different method to extract reflectivity from seismic trace data.](image)

As shown in Figure 3, the estimated reflectivity of the proposed method has a better consistency with real reflectivity compared with that corresponding to FISTA for large reflectivity in free-noise situation. Using the same parameters, FISTA can work well for some seismic traces but fails in others traces and generates false reflectivity (blue arrow in Figure 3). This implies that FISTA with fixed parameters cannot provide us satisfactory results in all situations. With reducing Signal-Noise Ratio (SNR) to 0 dB, the proposed method can preserve more details of reflectivity while FISTA can only depict large reflectivity and generate some artifacts (red arrow in Figure 3).

In this example, we apply Reflectivity-GAN to the 2D volume (Figure 4a) extracted from 3D field migrated seismic data. The migrated section contains 1001 traces and the time sampling interval is 2ms. As shown in Figure 4b, the resolution of the raw migrated section has been improved a lot after being processed by Reflectivity-GAN. Specifically, the thin-layer interference in raw migrated section that is difficult to be distinguished has been effectively separated. Meanwhile, the relative strength of amplitude is preserved.
Conclusions

In this paper, we proposed a Reflectivity-GAN based data-driven method for high resolution inversion of seismic data. Given wavelet, the mapping relations between reflectivity and seismic trace, can be gradually obtained through iterative training of generator and discriminator networks. The non-uniqueness of solution is reduced by constructing an objective function about the true reflectivity and the inversion result during the training process instead of the misfit between observed data and modeled data based on reflectivity as common methods do, which results in the inversion result to be more in line with the geological truth. Numerical examples based on both synthetic and field data verified the effectiveness of the proposed method and its advantages over conventional methods in estimating high-resolution reflectivity.

References


