Date-driven Seismic Velocity Inversion via Deep Residual U-Net

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Summary

Full-wave inversion (FWI) is an effective high-resolution imaging technique in seismic exploration, which is often criticized in three aspects: non-unique solution, cycle skipping and high computational cost. Recently, data-driven seismic inversion provides a powerful alternative strategy for conventional FWI. Its success greatly depends on a proper deep neural network architecture, which becomes a challenging problem nowadays for a limited number of training instances specially. In this abstract, we build a new seismic inversion network: ResUnet for velocity inversion. This network integrates the shortcut connections in residual network and concatenation connections in U-Net, into convolutional neural network, which can propagate useful discriminative information from the low level to the high level, and thus improve the network optimization procedure and inversion performance. On three synthetic data sets (Saltbody, Faulted and Layered), via quantitative comparison and visual analysis, we validate the effectiveness of our inversion network, via comparing with an existing method FCNVMB.

Introduction

Full waveform inversion (FWI) has become a key technique for high-resolution seismic imaging, which usually is criticized in three aspects: non-unique solution, cycle skipping and high computational cost (Yao et al., 2000). Therefore, many researchers aim to find out an alternative strategy to fulfill FWI. Recently, due to lots of successful applications and fast developments in machine learning field (Sarker, 2021), in deep learning specially (Menghani, 2023), some inversion approaches based on deep neural networks are chosen as an alternative strategy for FWI (Adler et al., 2021; Mousavi et al., 2024). As we know, velocity is one of the most important geophysical parameters in seismic exploration for oil and gas, which is used in the entire stage of seismic exploration from acquisition, processing to interpretation. Therefore, we focus on two-dimensional velocity inversion in this abstract.

Data-driven velocity inversion methods mainly consists of two steps: preparing a training instance set and training a deep network. In machine learning community, preparing a training instance set is to collect some instances and then annotate them manually (Sarker, 2021). However, this procedure does not hold true in seismic velocity inversion, since geophysicists and geologists could not exactly annotate a velocity profile for a given seismic record. To fit machine learning requirement, a compromised way is to design a series of velocity models and then create their corresponding seismic synthetic records, as labels and instances, respectively. So far, there are mainly three kinds of velocity models: Saltbody (Yang and Ma, 2019), Layered (Li et al., 2020), and Faulted (Zhang and Lin, 2020). Their corresponding instances are mainly multi-shot seismic records, which means to conduct a pre-stack inversion. The success of data-driven inversion also depends on deep network architectures. So far, convolutional neural networks with coder-decoder architecture are widely applied, for example, FCNVMB (Yang and Ma, 2019), InversionNet (Wu and Lin, 2020) and ResNet-ACE (Liu et al., 2022). The coder gradually decreases the height and width of feature maps, and increases the number of channels (or feature maps). Reversely, the decoder enlarges the height and width, and decrease the number of channels. It is widely-known that several successful applications of deep learning, for example, image recognition and natural language processing, extremely need lots of well annotated instances. However, it is intractable to create enough velocity models and their corresponding synthetic shot records for seismic velocity inversion. In this situation, with a limited number of training instances, it is challenging for constructing a proper inversion network architecture.

In this abstract, we regard two-dimensional seismic pre-stack velocity inversion from seismic multi-shot records to two dimensional velocity profiles as a heterogeneous image to image pixel level regression, and adopt residual U-net for image segmentation (Zhang et al., 2018) to our inversion task. Therefore a novel seismic pre-stack velocity inversion method based on residual U-Net is built, and simply as ResUnet. On three synthetic data sets (Saltbody, Faulted and Layered), via quantitative comparison and visual analysis, we validate that our ResUnet is effective and performs better than FCNVMB experimentally.

Two-dimensional Pre-stack Velocity Inversion Network Architecture Based on Residual U-Net

Two-dimensional pre-stack seismic velocity inversion infers a two-dimensional velocity profile from a multi-shot seismic record. Therefore, its input is a multi-shot record, indicated by a third-order tensor $\mathbf{X} \in R^{N_t \times N_r \times N_s}$, where N_t, N_r and N_s are the number of time sampling points, receivers and shots,

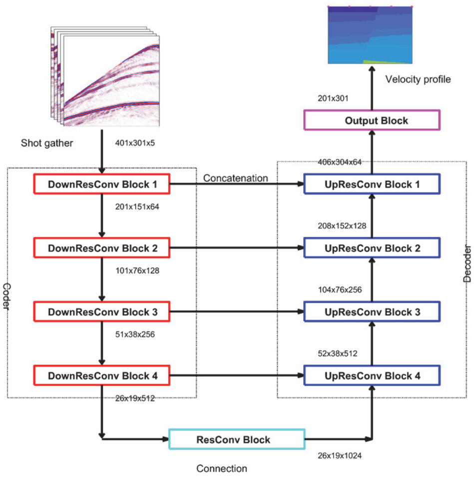

Figure 1: The entire architecture of our ResUnet.

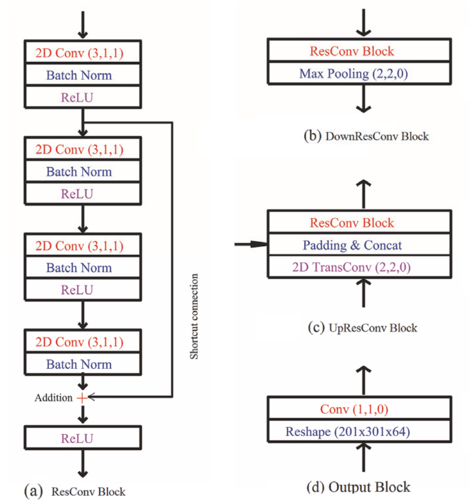

Figure 2: Four components for our ResUnet.

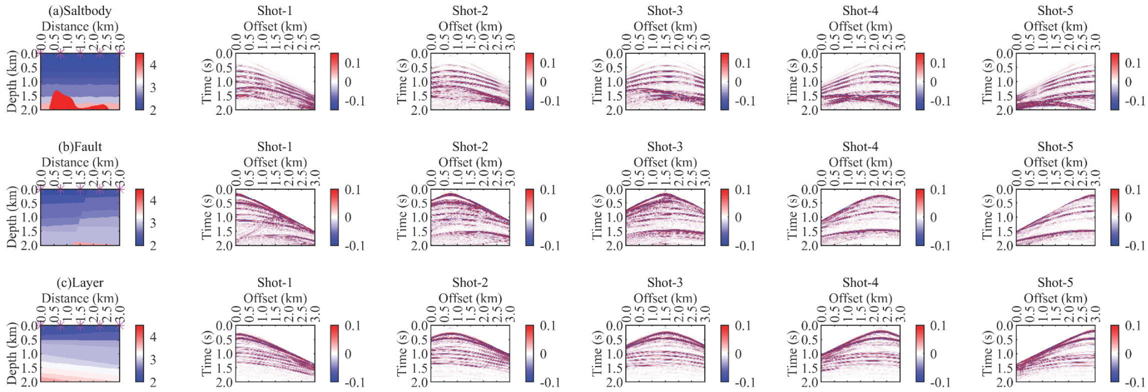

Figure 3: Three types of velocity models and their five shot seismic records.

respectively; and its output is a velocity profile, denoted by a matrix $\mathbf{V} \in R^{N_v \times N_h}$, where N_h and N_v are the number of gridding points along the vertical and horizontal directions, respectively.

Given a shot record, after initializing an initial velocity model, the conventional FWI creates a synthetic shot record, calculates the error between the given and created records, estimates the gradient of the error, and finally updates the velocity model with the gradient descent trick, until satisfying a stopping criterion. This inversion procedure is regarded as an individual-based strategy according to machine learning viewpoint. Data-driven inversion technique is a population-based strategy, which builds an inversion operator g: $\mathbf{X} \rightarrow \mathbf{V}$ directly, with a training instance set of the size M:

$$\{(\mathbf{X}_1, \mathbf{V}_1), \ldots, (\mathbf{X}_i, \mathbf{V}_i), \ldots, (\mathbf{X}_M, \mathbf{V}_M)\}$$

The objective is to minimize a mean squared error:

$$MSE = \frac{1}{2} \sum_{i=1}^{M} \left\| \mathbf{V}_i - g(\mathbf{X}_i) \right\|_F^2$$

where the symbol F indicates the matrix Frobenius norm. In this abstract, we will simulate this operator g via deep learning.

Our inversion problem is similar to image segmentation which annotates some interesting objects on an image. Recently, this problem is widely solved by U-net (Ronneberger et al., 2015; Ummadi, 2022). On the other hand, in image recognition, the residual net is a successful network (He et al., 2016). In (Zhang et al., 2018), these two representative networks are combined to construct a hybrid network: residual U-net or simply ResUnet for road

Table 1: Four evaluation metrics on three data sets from two algorithms

Metric	Saltbody		Layered		Faulted	
	FCNVMB	ResUnet(ours)	FCNVMB	ResUnet(ours)	FCNVMB	ResUnet(ours)
PCC(↑)	95.51±2.25	**97.50±1.25**	95.48±3.70	**98.11±1.12**	95.70±2.61	**98.02±0.86**
RMSE(↓)	213.28±49.21	**159.14±40.67**	112.23±43.66	**85.93±35.20**	139.15±43.49	**91.07±27.79**
PSNR(↑)	26.70±1.88	**29.28±2.05**	32.57±2.83	**34.88±2.78**	30.53±2.33	**34.21±2.35**
SSIM(↑)	91.55±1.63	**93.27±1.16**	96.24±1.21	**97.07±1.03**	95 22±1.20	**96.28±1.06**

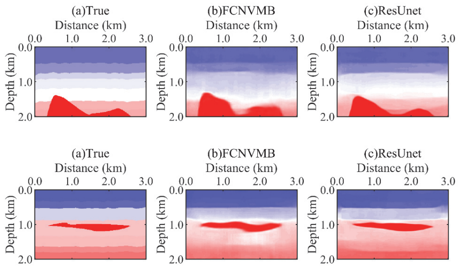

Figure 4: Two representative inversion models from Saltbody.

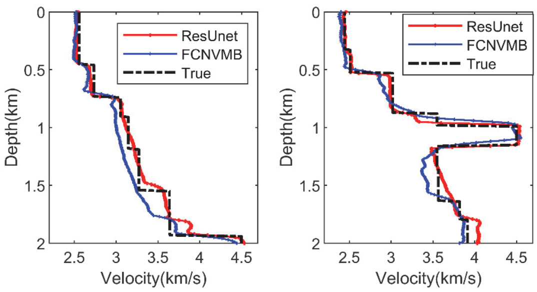

Figure 7: Velocity curves of middle trace in Figure 4.

recognition. We also observe that these three networks mainly deal with a binary classification problem.However, our inversion is essentially an image-image multi-output regression problem. In this abstract, we adopt this RenUnet to our velocity inversion task.

Our entire ResUnet architecture is shown in Figure 1, which consists of four parts: coder, connection, decoder and output. In Figure 2(a), we show residual convolutional (ResConv) block, which is composed of four convolutional black with three operations: 2D convolution, batch normalization and ReLU. It is noted that the addition operation is to add the output of the first block to the output of the fourth batch normalization via a shortcut connection. This special connection could avoid the possible gradient vanishing or explosion occurred in traditional back-propagation, and thus becomes the excellent characteristic of residual network. With this ResConv, we construct the DownResConv and UpResConv blocks. Each DownResConv includes a ResConv and a maximal pooling, as shown in Figure 2(b), where the latter would reduce the height and width half, and double the channels twice. Each UpResConv involves a 2D transpose convolution (TransConv), a padding and concatenation operation, and ResConv, as shown in Figure 2(c), where the TransConv expands the heights and widths, and reduces the channels, and Padding & Concat first adjusts the height and width from the DownResConv bolck and then executes the concatenation operation. The connection part only acts as a bridge between the coder and the decoder. Finally, the output block reshapes the heights and widths, and then reduces channels, as shown in Figure 2(d). In Figure 1, we also show how the height, width and channels vary gradually, through the entire network architecture.

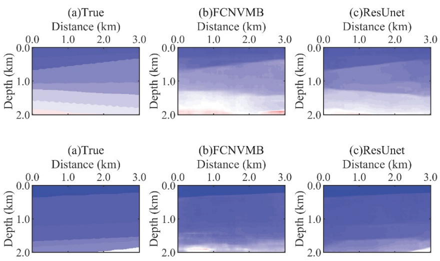

Figure 6: Two representative inversion models from Layered.

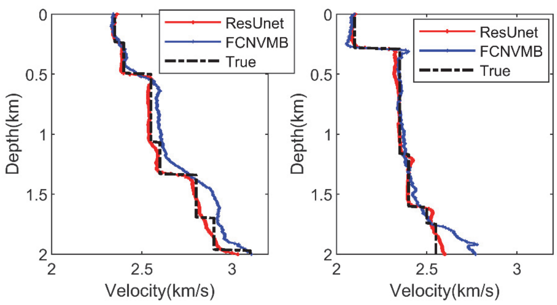

Figure 9: Velocity curves of middle trace in Figure 6

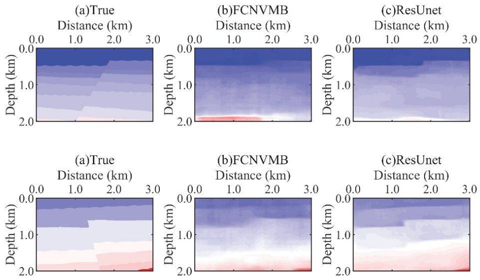

Figure 5: Two representative inversion models from Faulted.

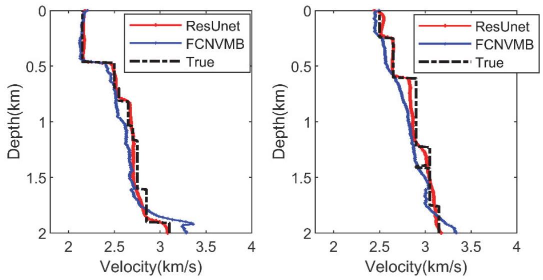

Figure 8: Velocity curves of middle trace in Figure 5.

Our method ResUnet is implemented and coded based on the Pytorch library (Paszke et al., 2019) and the corresponding optimizer ADAM (Kingma and Ba, 2015).

Experimental Results and Analysis on Three Types of Velocity Profiles

In order to validate our inversion network ResUnet, we collected three types of velocity models and their corresponding 5-shot seismic records (N_s=5) in (Yang and Ma, 2019; Li et al., 2020; Zhang and Lin, 2022), i.e., SaltBody, Layered and Faulted. In Figure 3, one velocity profile and their seismic record from each type are shown. The velocity model is 2KMx3KM, which is gridded in N_v=201 and N_h=301. The time length of acoustic seismic record is 2s and the sampling rate is 1ms, which is re-sampled with 5ms as in (Yang and Ma, 2019) and thus N_t=401. The 301 receivers are uniformly located on the surface of the Earth, and thus N_r=301. The ratio of training instances to testing ones is 1600:100, 1800:200, and 1800:200, respectively. Additionally, four metrics: Pearson correlation coefficient (PCC), root mean squared error (RMSE) (Borchani et al., 2015), peak signal noise ratio (PSNR) and structural similarity (SSIM) (Wang et al., 2004), are used to evaluate the performance of inversion algorithms. The compared algorithm is FCNVMB (Yang and Ma, 2019). After training our ResUnet and FCNVMB on training instances, we evaluate four metrics on testing instances, as shown in Table 1, where the upper arrow indicates that the better performance is high, and reversely for the down arrow. It is observed that our ResUnet is significantly superior to FCNVMB, as shown in the **bold** font.

In Figures 4-6, we show two representative predicted velocity profiles for three types of velocity models. Our predicted velocity profiles from ResUnet are clearer than those from FCNVMB, and are very close to the true velocity profiles. Moreover, in order to illustrate the predicted details more clearly, in Figures 7-9, the velocity curves of the middle (No. 151) traces are illustrated. Again, the predicted cures of our ResUnet are approximate to the true ones, and better than FCNVMB's.

Summarily, the above quantitative comparison and pictorial analysis demonstrate that the effectiveness of our proposed deep neural network architecture ResUnet for pre-stack seismic velocity inversion.

Conclusions

The progress in deep learning provides an alternative paradigm for pre-stack seismic full-wave inversion. In this abstract, we adopt the residual U-net to act as our seismic inversion architecture, which is verified by some extensive experiments on three types of velocity models: Saltbody, Layered and Faulted, via comparing to FCNVMB, according to four evaluation metrics (Pearson correlation coefficient, root mean squared error, peak signal noise ratio, and structural similarity) and visual comparison. Our work gives a new network architecture for data-driven velocity inversion. In the future, we will test more synthetic and real data to validate the performance of our proposed method further.

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