Well-log information assisted high-resolution waveform inversion based on deep learning

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Abstract—The high-resolution waveform inversion for seismic velocities is gaining increasing interest as we start to deal with complex structures. Although full waveform inversion has been used for several years, obtaining high-resolution velocity models still presents many obstacles, such as the high computational cost and the limited band width of the data. Thus, we propose a deep learning-based algorithm to build high-resolution velocity models using low-resolution velocity models, migration images, and well-log velocities as inputs. The well information, specifically, helps enhance the resolution with ground truth information, especially around the well. These three inputs are fed to an improved neural network, a variant of U-Net, as three channels to predict the corresponding true velocity models, which serve as labels in the training. The incorporation of well velocities from several locations is crucial for improving the resolution of the output model. Numerical experiments on complex models demonstrate the robust performance of this network and the crucial role that well information plays, especially in generalizing the approach to models that differ from the trained ones and achieving superior performance compared to full waveform inversion.

Index Terms—Seismic waveform inversion, Deep Learning, High-resolution, Well-log, Full waveform

I. INTRODUCTION

As oil and gas fields proliferate, high-resolution description of complex subsurface media becomes increasingly necessary. In recent years, high-resolution velocity inversion has, therefore, progressively gained more attention from the geophysical community. Full waveform inversion (FWI) has emerged as a promising high-resolution velocity inversion method. It aims to predict the subsurface velocity by iteratively minimizing the data misfits between simulated and observed data. Lailly [1] first proposed the time-domain FWI. By calculating the least-squares data misfits between synthetic and observed data, and updating the given initial model, they eventually produced an elastic velocity model.

Although Lu [2] shown that full-band FWI can produce a high-resolution velocity model, a number of challenges still exist. The first one is the computational cost of applying FWI on full-band seismic data, requiring a fine grid representation of the model space. Guo and Alkhalifah [3] applied a target-oriented inversion method in which they used velocity models extracted from low-frequency FWI to redact the data, then applied high-resolution inversion to the small reservoir area. Given the attenuative nature of the subsurface and the presence of noise, collecting ultra-high-frequency seismic data components that can be employed efficiently in FWI is a further challenge. Li et al. [4] introduced the use of well logs containing full wavenumber information to improve FWI resolution by deep learning (DL-) assisted regularization. Similarly, Li et al. [5] further proposed the use of DL-algorithms to map the relationship between the 1D profiles of FWI results and the available well-logs to achieve high-resolution inversion. The full-band wavenumber information of some locations supplied by well-log is anticipated to aid in high-resolution inversion, and a DL-algorithm provides a potential solution.

Deep learning is a data-driven algorithm with strong nonlinear mapping capabilities. The DL-based velocity inversion method is one of the prominent research that directly maps observed data to velocity models. Araya-Polo et al. [6], Wu and Lin [7], Li et al. [8], and others successively proposed the deep neural network (DNN) for seismic velocity inversion. All of the aforementioned networks employ pre-stack data as input and supervised learning to directly build the velocity, constituting the first generation of DL-based seismic velocity building methods. Sun et al. [9] and Jing et al. [10] improved the structural accuracy of results by including physical rules based on wave equations into DNN, with the latter achieving unsupervised learning inversion. However, these methods that directly predict the velocities from seismic data are highly dependent on training samples and are difficult to generalize to distributions other than those they were trained with, posing challenges for their future application on real data. As a result, several methods have recently been proposed to predict low-wavenumber velocities using migration images or low-frequency data, and to predict accurate velocities with background velocities improved migration images or high-frequency data [11], [12]. However, the input data they provide to the network do not include full-band wavenumber, which diminishes the reliability of the predictions.

This letter presents well-log assisted high-resolution waveform inversion based on deep learning as a solution to the high computational cost and generalization challenges. Specifically,
we take the low-frequency (LF-) FWI inversion results $v_{LF}$ obtained after a few cheap iterations, the high-frequency (HF-) migration images $I_{HF}$ with $v_{LF}$ as the background model, and the available well logs that potentially provide full-band wavenumber information as inputs to the network. It allows better performance and generalization by introducing more information and performing waveform inversion in the model domain compared with the classical DL-based inversion method. We improved the DNN structure for velocity building with reference to U-Net and compared it with and without well logs as input, with the classical U-Net using well logs. Moreover, the generalization of the proposed method has been surprisingly well performed and improved over FWI.

II. A FULL WAVEFORM INVERSION BACKGROUND

In recent years, FWI has become a research hotspot in the field of seismic exploration, being primarily used to obtain high-resolution velocity models. As shown in Fig. 1, for the traditional seismic inversion and imaging workflow, the kinematic information in data is effectively utilized to obtain a smooth velocity model using tomography. This tomographic velocity model is then used as a background model to image the seismic data, providing high-resolution structural information. There is an obvious gap between tomography results and migration images in the wavenumber spectrum, and the linear nature of the imaging kernel makes it vulnerable to multiple artifacts. FWI provides a solution to fill this gap and address multi-scattering.

![Fig. 1. A diagram showing the wavenumber spectrum of the true velocity and those obtained from seismic processing.](image)

In traditional FWI implementations, the residuals between the synthetic data $d_i$ and the observed data $d_{true}$ are used as the adjoint source to compute the gradient and update the velocity $m_i$, until we converge to a high-resolution velocity model. The spatial resolution of FWI result is often analyzed in terms of the wavenumber. For the velocity model $m$, the spatial resolution of FWI depends on the frequency of seismic data $f$ and the subsurface scattering angle $\theta$, and their relationship with the model wavenumber $k$ at a point $(x, y)$ in the model is described as follows:

$$k(x, y) = \frac{4\pi f m(x, y) \cos \left( \frac{\theta(x, y)}{2} \right)}{x}. \quad (1)$$

Therefore, the increase of resolution in FWI is linked to high-frequencies and small scattering angles [14]. Bunks et al. [15] proposed a multi-scale FWI method to alter the frequency band of seismic data through low-pass filtering, in which FWI is first applied on the low-frequency data and higher frequencies are gradually included. Referring to Fig 1, it may be understood as a process of gradually completing the velocity information from low to high-wavenumber to ultimately obtain high-resolution models. However, the cost of high frequency FWI and the limits on the seismic data frequency band, especially from deeper targets, limit our ability to obtain high-resolution velocity models.

Deep learning algorithms are regarded as a viable option for reducing computational cost, but suffer from poor generalization in most of recent works. The limitation on the seismic data frequency band can be addressed by the availability of high-resolution well information.

III. METHODOLOGY

A. Well-log Assisted High-Resolution Inversion Based on DL

In this study, a network is trained to map a low-resolution velocity model obtained from LF-FWI along with the corresponding image and well-log information to an accurate velocity model. From the angles of multi-scale FWI and wavenumber analysis, we plan to complete the full wavenumber information from three perspectives as far as possible.

First, with the low-wavenumber tomography result as the initial model, the low-resolution velocity model can be obtained by performing several iterations on the low-frequency data, with a cheap computational cost, which can be regarded as the first component of multi-scale FWI. Then, using this as the background velocity, the RTM image for high-frequency data is computed to provide high-wavenumber information. In other words, we obtain representations of the low- and high-frequency data bands, which are used to build the true velocity model with the help of deep learning to accelerate the computation. In addition, considering that ultra-high-frequency data is often unavailable, especially for the deep part of the subsurface, we also use well logs as input to the network. Well-log data inherently has broad band wavenumber information at some locations, offering a guide to enhance the wavenumber content throughout the network. In short, the above framework can be formulated as follows:

$$v_{hf} = \text{FWI} (v_{initial}, d_{LF}),$$

$$I_{hf} = \text{RTM} \left( v_{LF}, d_{full-band} \right),$$

$$v = \text{Net} \left( \theta, v_{LF}, I_{HF}, W \right), \quad (2)$$

where $\text{Net}()$ denotes the mapping of the network, whose learnable parameters are $\theta$, and $W$ is the given well-log velocity image. An example is shown in Fig 2, in which the well velocity information is placed at well locations within an image and the rest of the image is set to zero. This image, of the same size as the velocity and migration image, occupies a third channel of the network input. This approach to injecting the well-logs allows for flexible well configurations and numbers to be used.

From the computer vision perspective, we consider the low-frequency inversion result as a blurred version of the velocity, while the migration image may help in providing edge information for the velocity. Similarly, the introduction of well-log information can help connect the two model scales of information, which span the full model to the true velocity.

B. Improved Network

Referring to the classical U-Net and the previously proposed SeisInNet [8], a variant U-Net is employed as shown in Fig 2.
Fig. 2. The proposed network structure. The Conv Block consists of a convolution with a kernel size of 5×5, batch normalization, and an activation function. The orange blocks represent the features obtained by the encoder; the blue blocks represent the features obtained by the decoder. The four green blocks correspond to the feature maps extracted by different dilated convolutions, and finally, they are concatenated together and extracted by a layer of convolution blocks for the next step, which is the black block that is finally used to predict the velocity model. The number above the block is the number of channels.

Similar to U-Net, we also use an encoder and a decoder to build the velocity model and introduce the skip connection to maintain previous features. The convolution block (Conv Block) consists of the convolutional layer with a kernel size of 5×5, batch normalization, and the activation function, ReLU, except for Sigmoid used in the last layer of the decoder. In contrast to U-Net, the improved network achieves compression of the features by convolutions with stride 2 instead of downsampling; in the decoder, up-sampling and convolution are used to restore the scale, and the channels are reduced to a quarter. Then, four different dilated convolutions with 3×3 kernel are used to extract structural information at different scales, which improves the accuracy of predictions. Additionally, the mean square error (MSE) and multiscale structural similarity (MSSIM) are naturally selected as loss functions and evaluation metrics for the whole model.

IV. EXPERIMENTS

A. Dataset Preparation

For supervised learning algorithms, the training dataset often influences the accuracy of the results and generalization. In this study, using the model generation method presented by Ovcharenko et al. [16], a laterally homogeneous layered velocity model is generated from a sparse sequence of simulated impedances as a function of depth, and then an elastic transformation is applied to distort the model and rescale the velocities randomly. The size of generated models is set to 3.2 × 9.2 km with a grid size of 20 m and a velocity range of 1.5 to 5.5 km/s. Then, 2000 sets of models are used and separated into the training, validation, and test sets in a ratio of 8:1:1. Between two to five vertical profiles are randomly selected from the true velocity model to represent well locations, which are fixed for each model during network training. To demonstrate the generalization of the proposed method, we use the Marmousi model and nine 2D slices from the Overthrust model, which are not used in the training process.

Deepwave [17] is used to implement forward modeling, FWI, and RTM with GPU parallelism. Specifically, a Ricker wavelet with a peak frequency of 12 Hz is used as the source. A total of 20 sources and 460 receivers are uniformly deployed on the surface. The time steps and time intervals are set to 6000 and 1 ms, respectively. Gaussian smoothing is used to obtain the initial model for the low-frequency FWI. In previous work [18], [19], it has been demonstrated that a smoothing model can be employed as the initial model for high-resolution inversion, and equivalently the tomography result as an initial model for field data. For field data, satisfactory initial models can also be obtained from surface-waves [20]. In our implementation, we reduce the dependence on the initial model since low-frequency FWI is utilized to obtain the input to the network. A band-pass filter between 2 and 5 Hz is applied to extract low-frequency data, which reflects our inability to acquire usable low-frequency data in real situations. In addition, thanks to the benefits of Deepwave, an Adam optimizer with a learning rate of 20 is utilized to update the velocity models, which has been shown to provide the best performance [21] and the less computational cost. The inverted LF-FWI result is used as the background velocity for the full-band seismic data to calculate the high-wavenumber migration images. The workflow is shown in Fig 3.

B. Results from Different Networks and Inputs

To demonstrate the impact of the introduced well-log information on the high-resolution velocity prediction, we compare the effect of the network with two channels (v<sub>f</sub> and I<sub>f</sub>) and three channels of information (u<sub>f</sub>, I<sub>f</sub>, and W) as input. To focus on the incorporated well information, we use the exact same network with the exception of the network input channels (3 vs 2). To highlight the superiority of the proposed network over the often used U-Net in previous research [11] and classical DL-inversion method, we also compared it to U-Net and SeisInvNet [3]. Table I shows the performances of four
models, are supplemented in addition to the normal test set, distribution datasets, namely the Marmousi and Overthrust barrier. This study works on improving the generalization of the fact that transfer learning may address this issue using deep learning-based velocity inversion methods. Despite C. Generalization and Comparison with FWI

In achieving uniform interlayer velocity models. Resolution formations, and the improved network is effective in predicting high-frequency well-log information contributes to the prediction of detailed high-resolution results for complex models of large size that we do not show its results subsequently. Qualitatively, Fig. 5 depicts the prediction results of the three methods on a randomly selected model on the test set. Overall, all three methods obtain satisfactory results since the slightly accurate low-frequency inversion results are used as inputs. Affected by the receptive field of the convolutional neural network, the introduced well-log information induces some high-resolution structural information not only at the well log locations, but also in the vicinity of the well logs. As shown in the black dashed box in the first row, it is difficult to obtain the abrupt variation of velocity without the introduction of well-log velocity, but our method improves the prediction effect in the vicinity and achieves higher resolution. The U-Net is incapable of eliminating the artifacts in the low-frequency FWI results, which are better attenuated in our network.

Thus, from the above analysis, we conclude that high-resolution results can be obtained with higher accuracy when well-log information is incorporated. This proves that the well-log information contributes to the prediction of detailed high-resolution formations, and the improved network is effective in achieving uniform interlayer velocity models.

C. Generalization and Comparison with FWI

Generalization has been a persistent problem to be tackled by deep learning-based velocity inversion methods. Despite the fact that transfer learning may address this issue using a small amount of labeled data, access to labels remains a barrier. This study works on improving the generalization of the network in terms of both task design and the training dataset. In evaluating the network performance metrics, other distribution datasets, namely the Marmousi and Overthrust models, are supplemented in addition to the normal test set, for which transform learning is not required. The performance of the inversion results and comparison with FWI on the other distribution models are shown in Fig. 5.

For the direct prediction results, as shown in Fig. 5(b), our method achieves satisfactory results on the Overthrust model. After providing the two well velocity profiles, the result is almost consistent with the actual model at shallow depths, which is usually difficult to obtain for direct network prediction. For velocity structure at depth, the low-resolution velocity model given does not provide an accurate background velocity distribution, resulting in less than satisfactory predictions. But the velocity is still accurate near and in the well logs, which shows that the well logs are very important for obtaining the full wavenumber signal. Similarly, for the more complex Marmousi model, as shown in Fig. 5(g), our method still substantially improves the error in the prediction results, despite the fact that the given low-frequency inversions are poor. Also, due to the given well-log information, the velocities near the well logs have high reliability, which will also help us extrapolate to other locations. Given that our method employs direct prediction, no transfer learning is needed, drastically reducing the computational cost. High-frequency FWI may continue to optimize the network’s predictions, and our work will considerably shorten the computation time of FWI.

To show the advantages in comparison with FWI, we performed FWI using Deepwave with the same parameters for three strategies, whose implementation and computation time are shown in Fig. 6. For our method, network training time is not included, since the trained network is directly employed for subsequent prediction and no transfer learning is needed. Compared to FWI (a), our method delivers results that are far superior to the classical FWI in terms of structure, resolution, and MSE, while requiring less computing time. In reality, this is because the LF-FWI results used as initial models make it hard to obtain an accurate estimate of the high velocity regions using full-hand data, such as the high velocity region on both sides of the Marmousi model. As noted in the fourth column, FWI (b), the use of a multiscale strategy significantly mitigates this issue, particularly as seen in Fig. 5 (d). The introduction of the multi-scale strategy increases the computational cost, which is more than eight times longer than our method without achieving total better performance, thus proving the value of our method. In addition, FWI results using network predictions as the initial model eliminated the inaccuracies in our results and enhanced the accuracy in comparison with the multi-scale FWI results, see Fig. 5(e) and (j). The added cost is equivalent to one-third of the calculation time of multi-scale FWI.

Finally, for more experiments and discussion on the influ-
In this study, we carried out a deep learning-based high-resolution seismic velocity inversion with the assistance of well-log information. We can use a low-frequency velocity model (often utilized for cost purposes) and the corresponding full-band image using that velocity as inputs to the network to predict the true high-resolution velocity model. On the other hand, to further provide effective high-resolution information, we consider the introduction of well-log velocities to help guide the network to accurate high-resolution models when applied to other datasets. To do so, we used an improved variant of U-Net with low-frequency FWI models, high-frequency RTM images, and sparsely-distributed well logs as three channels of inputs to the network to predict the true velocity model. The performance of the trained network greatly benefits from the introduced well-log information, and more well logs often result in an inverted velocity model with higher accuracy. Due to the network’s mapping in the model domain and the improved dataset, the trained network achieves a promising performance on other distributed datasets of the application, and no transfer learning is required. The network performs even better than the widely acclaimed multi-scale FWI, especially for a small number of iterations of the predicted results, which achieves better results with much less computational cost than a typical FWI.

VI. ACKNOWLEDGMENTS

We acknowledge the seismic wave analysis group members for their fruitful discussions and helpful suggestions and KAUST for support. We are also grateful to Oleg Ovcharenko and colleagues for their complex model building methods.

REFERENCES


