Introduction

Elastic full waveform inversion (EFWI) aims to estimate the elastic properties with reasonably high resolution in hope of providing information useful for reservoir characterization. However, due to the limitation of surface seismic data in terms of signal-to-noise ratio (SNR), frequency band and offset, seismic data often admit incomplete subsurface information with limited space wavenumber (Alkhalifah, 2016; Li et al., 2019).

High-resolution well logs can compensate for the lack of illumination provided by seismic data where the well is used as a model-space regularization (Asnaashari et al., 2013). The key problem is how to link the high-resolution well information to the subsurface model estimated from EFWI. Asnaashari et al. (2013) built a prior model by interpolating the well velocities and gradually decreased the weight for the prior model during inversion. Zhang et al. (2018) employ Bayesian theory to invert for a facies map by maximizing the posterior probability using the L2-norm inversion result and the predetermined facies information. In a similar way, Singh et al. (2019) constrain the inversion workflow using a prior model derived from facies distribution and the available well logs. Zhang and Alkhalifah (2019) employ deep neural networks (DNNs) to build the proper statistical connection that converts seismic estimates to facies interpreted from well logs. They use $v_p$, $v_s$ and their ratio as discriminant features of facies extracted from well logs. However, the high-resolution components of well velocities are hard to preserve because of the averaged properties within facies. To retain the high-resolution information of well logs, we include the mean and variance of $v_p$ and $v_s$, computed in a Gaussian window, as the discriminant features. The derived high-resolution prior model is added to EFWI as a regularization term. We use synthetic data and 2D OBC field data to demonstrate the effectiveness of the proposed method.

Theory

EFWI aims to minimize the residuals between the observed and simulated data at the receivers using an iterative local-optimization scheme. To mitigate the ill-posedness of the inverse problem, prior information from other geophysical methods, such as well logs, is included in the objective function as a regularization. We define the objective function as a combination of a standard data misfit term and a model misfit term:

$$ J(m) = J_d(m) + \beta J_w(m), $$

where, $\beta$ is a weighting parameter balancing the contributions from these two terms.

The data misfit term is defined as a L2 norm of the data residuals:

$$ J_d(m) = \| W_d (d(m) - d_o) \|^2, $$

where, $d(m)$ denotes the predicted data determined by the model $m$ using the elastic wave equation, $d_o$ is the observed seismic data and $W_d$ is a weighting matrix for the data.

The model misfit term measures the deviations from a prior model:

$$ J_w(m) = \| W_m (m - m_{\text{prior}}) \|^2, $$

where, $W_m$ is a diagonal matrix. $m_{\text{prior}}$ is a high-resolution prior model which incorporates prior information from well logs.

Building a Prior model assisted by DNN

We derive a prior model by connecting the inverted model to interpreted facies from wells using a supervised learning method, specifically, a deep neural network (DNN). A deep neural network consists of input and output layers, with fully connected hidden layers in between. The number of hidden layers and neurons of each layer is adjusted according to the size of the training dataset. Details of the DNN used in the examples will be explained in the examples sections. We applied the synthetic minority over-sampling technique (SMOTE) to enlarge the training datasets and reduce the imbalance of different facies (Chawla et al., 2002). We also employ a random dropout of 30% to avoid over-fitting.
The DNNs-based classification of facies is implemented by discriminating the selected features of facies. We include means and variances of $v_\text{p}$ and $v_\text{s}$, defined in a Gaussian window, as the discriminant features, i.e., $(\mu_\text{p}, \sigma_\text{p}, \mu_\text{s}, \sigma_\text{s})$. Interpreted facies from the well logs are used as the labels in the training. Once this training is finished, the DNN establishes a mathematical connection between the features of inverted model and various facies classes. We can apply the network to the whole inversion region to predict the facies for every model point. The output for every point is a single vector $\mathbf{p} = (p_1, \ldots, p_{\text{nf}})$, each element represents a probability that a model point is categorized as facies $i$. Given the probability distribution, we can compute the expectation by a weighted summation over facies as the predicted features (mean and variance fields) as follows:

$$
(\mathbf{\mu}_\text{p}, \mathbf{\mu}_\text{s}, \mathbf{\sigma}_\text{p}, \mathbf{\sigma}_\text{s}) = \sum_{n_{\text{face}}} p_i (\mathbf{\mu}_{n_i}, \mathbf{\sigma}_{n_i})
$$

The high-resolution prior model can be recovered by solving the following optimization problem.

$$
\mathbf{m}_\text{p} = \arg \min_{\mathbf{m}_\text{p}} \frac{1}{2} \sum_{n, \tau} \left[ m_p(x, z + \tau) - \mathcal{P}(x, z) \right]^2 + \lambda \sum_{n, \tau} \left( m_p(x, z + \tau) - \mathcal{P}(x, z) \right)^2 \mathcal{G}(\tau) d\tau - \mathcal{G}(x, z)
$$

where, $\mathcal{G}(\tau)$ is a normalized Gaussian smoothing operator, and the width $w_\tau$ is set as 10 in the examples. Lastly, we implement the regularized EFWI by incorporating the prior model into the inversion workflow.

**Otway synthetic example**

We first apply the proposed method to part of the Otway model (Figure 1). The initial model is a smoothed version of the true model using a Gaussian smoothing window of 100m width. We first use the 2-15Hz frequency band to implement conventional EFWI, and the inversion result is shown in Figure 2. We can see that the spatial resolution is consistent with what we would expect from FWI for the band used, as the thin layers are hardly captured. The high-resolution information can be boosted by using well logs. Three vertical profiles of the true model at 0.3, 1.2 and 1.7km are taken as the pseudo wells. We extract 20 facies from the three wells according to their different features in mean and variance. The deep neural networks contain 6 hidden layers and they have 256, 256, 128, 128, 64, 64 neurons, respectively. The network is trained to build a mathematical relationship between the inverted velocities (Figure 2) and the interpreted facies labels. We then apply the network to the whole inversion region and recover the prior model using the proposed formulations. The regularized EFWI result using the prior model contains significant details and high-resolution components as shown in Figure 3. The data misfit term doesn’t decrease much because the 2-15 Hz frequency band data are not sensitive to the captured high-wavenumber component. We further implement EFWI with total variation (TV) regularization using higher frequencies of 2-40Hz starting from the regularized EFWI result (Figure 3). The inverted velocities shown in Figure 4 still reveal more details compared to those starting from Figure 2, which can be seen from the comparison of their vertical profiles at x=1.5 km (Figure 5). The evolution of data misfits (frequency band 2-40 Hz), shown in Figure 6, indicates that the proposed method improves the data matching.

![Figure 1](image-url) The true model. P-wave (a) and S-wave (b) velocities.
Figure 2  The conventional EFWI result. P-wave (a) and S-wave (b) velocities.

Figure 3  The regularized EFWI result assisted by DNNs. P-wave (a) and S-wave (b) velocities.

Figure 4  The EFWI result with TV regularization using a frequency band of 2-40 Hz starting from DNNs-aided EFWI result shown in Figure 3. P-wave (a) and S-wave (b) velocities.

Volve field example

We apply the proposed method to a 2D line from Volve OBC field data. The initial model (Figure 7) is derived by smoothing the provided tomography model. The target reservoir at 3.0 km depth is obviously smeared. We use the frequency band 2-10 Hz in the inversion workflow. The conventional EFWI result is shown in Figure 8. The reservoir with low velocities is delineated, but with limited resolution. We then interpret 10 facies from the provided well log and train the deep neural networks, which has 4 hidden layers with 64 neurons in each of them. After training, we apply the prediction to the whole inverted model. Using the derived prior model, we further conduct regularized EFWI (Figure 9). The resolution is improved and the velocity model reveals more details of the reservoir. We also compare the vertical profiles of inverted velocities near the well with well velocity in Figure 10. The proposed method can improve the matching between the inverted and well velocities.

Figure 5  Comparison of a vertical profile at x=1.5km.

Figure 6  Evolution of the data misfits for the EFWI using the 2-40 Hz frequency band.
Figure 8 The conventional EFWI result. P-wave (a) and S-wave (b) velocities.

Figure 9 The regularized EFWI result assisted by DNNs. P-wave (a) and S-wave (b) velocities.

Figure 10 Comparison of the vertical profile at the well location.

Conclusions

We develop an EFWI scheme to estimate high-resolution elastic properties by incorporating the well information into the inverted model using trained DNNs. The mean and variance of the velocities, defined in a Gaussian window, is utilized as the discriminant features for facies. The DNNs connect the inverted model and facies extracted from well logs from a statistical perspective. The high-resolution prior model can be recovered from the predicted mean and variance values. The numerical examples show that the proposed method improves the model resolution and consistency with well logs.

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References


