Deep learning Q inversion from reflection seismic data with strong attenuation using an encoder-decoder convolutional neural network: an example from South China Sea

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Outline

- Introduction
- Method and theory
- Field data application
- Conclusion
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Problems of attenuation

- Amplitude decay
- Poor illumination
- Unreliable AVO

A seismic image with strong Q effect

(Zhou, 2011)
The Q effect

Attenuation classification

Quality factor that quantifies seismic attenuation

- Small Q means large attenuation
- Strong attenuation: $Q \sim 10-50$
- Mild attenuation: $Q \sim 70-300$
- Nearly no attenuation: $Q > 1000$
Effect of attenuation on amplitudes

Amplitudes
- The higher frequencies of a wave are attenuated more than its lower frequencies
Effect of attenuation on phase

Phase
- The higher frequencies of a wave travel faster than its lower frequencies.
Effect of attenuation on imaging

Migration without Q compensation
- Damps amplitudes
- Lowers resolutions
- Disperses phases

Without Q compensation

With Q compensation

Courtesy of CNOOC
Effect of attenuation on reservoir characterization

(Chen et al., 2016)
Effect of attenuation on reservoir characterization

(Francis, 2016)
Approach to compensate Q effect

1. Filtering method

Nonstationary Deconvolution

（Dasgupta and Clark, 1998; Margrave et al., 2003, 2011; van der Baan, 2012）

Poststack inverse Q filtering

（Bickel and Natarajan, 1985; Hargreaves and Calvert, 1991; Wang, 2002）

Prestack inverse Q filtering (Wang, 2006; Cavalca et al., 2011)

Q inversion and compensation

（Causse et al., 1999; Reine et al., 2012; Chen et al., 2013; Wang and Chen, 2014; Li and Liu, 2015; Chai et al., 2016）

Limitation: Simple Q model used, can not handle heterogeneous Q model well.
Approach to compensate Q effect

2. Q compensation through Pre-stack migration

Ray-based (Ribodetti et al., 1998),

One way wave equation

(Dai and West, 1994; Mittet et al., 1995; Yu et al., 2002; Mittet., 2007; Zhang et al., 2013; Shen et al., 2014)

Two way wave equation

(Causse and Usin, 2000; Deng and McMechan, 2007, 2008; Zhang et al., 2010; Yan and Liu, 2013; Zhu et al., 2014)

Challenge: Needs a fine heterogeneous Q model in depth domain
Q-PSDM: accumulated Q effect along raypath

Back-project the amplitude variations along raypaths

\[ A(l) = A_0 \exp \left( -\frac{\omega l}{2vQ} \right) \exp \left( i \frac{\omega l}{2vQ} \ln \frac{\omega}{\omega_h} \right) \]

\[ \text{Amp}_{\text{attenuation}} = \exp \left( -\frac{\omega}{2} \sum_{\text{raypath}} \frac{l}{vQ} \right) \]

(Zhou, 2011)
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Traditional Q estimation approach
-- Spectral ratio method

\[
\ln\left( \frac{R_1}{R_2} \right) \\
\rho \sim -\frac{1}{Q}
\]
Traditional Q estimation approach -- Centroid frequency shift method

\[ Q = \frac{\sigma_s^2 \pi \Delta t}{f_s - f_R} \]

Where \( f_s \) and \( \sigma_s^2 \) are the centroid frequency and variance of source wavelet, respectively. \( f_R \) is the centroid frequency of received amplitude spectrum. The expressions

Fig. 10. A synthetic test on 2-D attenuation tomography. (a) is the original model. There are two low Q-value areas in this model, and (b) is the reconstructed Q-value distribution.

(Quan and Harris., 1997; Li et.al., 2015)
Recent Q estimation approach -- Image domain WE migration Q analysis

Define $\rho$ as the effect of attenuation (effect of Q) on seismic migrated images.

$$J = \frac{1}{2} \sum_x |\rho(x; Q)|^2$$

$x$ is each a spatial location in the image space. $Q$ is the current model for quality factor.

(Shen et al., 2018)
Recent Q estimation approach -- image domain WE migration Q analysis

- Large scale industry problem
- Sensitive to noise

(Shen et al., 2018)
ML and DL in Geophysics

Good at solving the problems of classification, clustering, regression and dimensionality reduction of high-dimensional data

First break picking, VA and FWI, Fault, horizon and salt dome identification, Classification of phases...
Work Flow

Data and Network preparation

- Migration to output seismic image
- Dividing datasets to training, testing, Validation set.
- Labelling the data by hand picking
- Constructing the structure of neural network, choosing number of network layers, input neurons, the activation function, loss function and optimization method.

Network training and data validation

- Training the network using the training set with labels, adjust the network structure based on the performance of the cost function.
- Verify network parameters, complete network training, using test data to check generalization effect.
- Input the whole dataset, finish automatic Q inversion and imaging with the Q field.

Network training is most time-consuming
CNN architecture for Q inversion
The depth and width of hidden layers decide the learning ability of a NN.

Too simple NN causes underfitting.

Over complicated NN causes overfitting.

Through testing, we choose the number of layers at 4.

The diagram compares the training error and the validation error with training time.
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The 3D seismic data
The Q inversion result
The Q-PSDM method to verify

Imaging result

\[
I(x, y, d) = \left(\frac{A_i}{A_s}\right)^2 \int F(\omega) \exp\left(-j\frac{\pi}{2}\right) \exp\left[j\omega\left(\tau_s + \tau_g\right) - \ln(\omega/\omega_0) \left(\frac{\tau_s + \tau_g}{Q_s/Q_g}\right)\right] \exp\left\{\frac{\omega}{2} \left(\frac{\tau_s}{Q_s} + \frac{\tau_g}{Q_g}\right)\right\} d\omega
\]

Weights  3D effect  Traveltime

Phase correction  Amplitude compensation

Compensating Q effect
The migration gather w/o Q compensation
The imaging result w/o Q compensation
Result comparison: Spectrum

About 15 Hz main frequency lifting
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Conclusions

• The DL method can help to capture the Q anomaly automatically after network training.
• The proposed Q model building workflow is less affective by the noise and suitable for large-scale industrial problems.
• Automatic labeling is the topic that needs further study.
THANK YOU!