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Robust joint imaging and tomographic Q-estimation based on full wavefield matching using a machine learning constraint

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Summary

Seismic wave attenuation, quantified by the quality factor (Q), leads to energy loss and waveform distortion, significantly degrading seismic data quality and resolution. Accurate Q estimation is essential for understanding subsurface properties, particularly in applications such as carbon capture and storage (CCS) and near-surface studies, where attenuation effects are pronounced due to the presence of fluids, gases, or loose soil. Traditional Q tomography methods predominantly rely on spectral-ratio or centroid-frequency shift approaches to account for attenuation effects. However, these methods often face significant limitations, including oversimplified wave propagation assumptions, poor localization in heterogeneous media, and a tendency to produce smeared results, ultimately reducing resolution and accuracy.

To address these challenges, we introduce a novel Q-estimation approach that integrates full-waveform matching for accurate attenuation-effect estimation and compensation during the migration process. The Full Wavefield Migration method is enhanced by incorporating Q into a one-way modeling operator, utilizing full-waveform matching for precise Q estimation, and applying a Random Forest regression constraint to mitigate cross-talk between Q and reflectivity. This approach enables robust and localized Q estimations. Numerical examples demonstrate its effectiveness in accurately retrieving both reflectivity and attenuation models, thereby improving imaging resolution in complex subsurface environments.

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Introduction

The propagation of seismic waves through the Earth's subsurface is influenced by various attenuation mechanisms that lead to significant energy decay and waveform distortion. These effects degrade seismic data quality, compromising the resolution and reliability of imaging and inversion processes.

Intrinsic attenuation of P-waves, quantified by the quality factor Q, represents the gradual energy loss of seismic waves during propagation. Lower Q values indicate greater energy loss per wave cycle, reflecting higher attenuation. This attenuation is inherently linked to dispersion, which shifts energy toward lower frequencies, causing waveform broadening and distortion over time (Aki and Richards, 2002). Accurate estimation of Q is essential for high-resolution seismic imaging, as it provides critical insights into subsurface properties, including lithology and the presence of fluids or gases—key factors in exploration and monitoring applications. In the context of the energy transition, such as carbon capture and storage (CCS) and near-surface studies, Q estimation becomes even more significant. CCS sites often feature attenuative regions due to the presence of gas and fluids, while near-surface areas exhibit higher attenuation due to the loose nature of the soil. Therefore, developing reliable methods to account for attenuation effects in imaging is crucial for ensuring accuracy in these applications.

In Q tomography methods, cross-talk between Q and other parameters in full-waveform approaches remains a significant challenge. As a result, Q tomography methods predominantly rely on spectral-ratio or centroid-frequency shift approaches to account for attenuation effects (Shen et al., 2018) instead of full-waveform matching. While these methods may be less sensitive to cross-talk, they often oversimplify wave propagation by neglecting the complexities of full-waveform modeling and relying on synthetic or reference models, which limits their effectiveness in heterogeneous media. Additionally, they tend to produce smeared results, making Q estimations based on spectral analysis comparisons that are generally not highly tomographic or well-localized.

While conventional Q tomography methods often rely on frequency spectral analysis, in this work, we propose an approach that utilizes full-waveform matching for accurate Q-estimation based on residual data and compensates for it during the migration process. Our main purpose in this study is to find a robust way to estimate and compensate for anelastic attenuation effects to improve the Full Wavefield Migration method's ability to provide higher seismic resolution in complex areas. Our method achieves robust and localized Q-estimation by integrating Q in a one-way modeling operator, using full waveform matching, and employing a random forest constraint to mitigate cross-talk between Q and reflectivity. It is fully tomographic, overcoming the limitations of conventional techniques.

Theoretical Framework of FWM: Integrating Q Effects and Random Forest Constraints

The Full Wavefield Migration (FWM) method (Berkhout, 2014b; Davydenko and Verschuur, 2017) is an inversion algorithm that updates the subsurface reflectivity model to match actual seismic data, employing a gradient descent method. FWM utilizes the Full Wavefield Modeling (FWMod) (FWMod, Berkhout, 2014a) methodology, which uses one-way propagators that rely on phase-shift techniques, such as the phase-shift plus interpolation (PSPI) method (Gazdag and Sguazzero, 1984). In our work, we use a nearly constant-Q model (Futterman, 1962) to estimate seismic wave attenuation during migration, which operates under the consideration that Q is almost frequency-independent. The one-way wave equation for viscoacoustic modeling, introduced by Futterman (1962), looks similar to the acoustic wave equation, but it uses a complex number to represent slowness, as follows:

$$s_c = \mathrm{s}\left(1 - \frac{A}{\pi}\ln(\omega/\omega_0)\right)\left(1 + \frac{iA}{2}\right). \tag{1}$$

Equation 1 involves the variables s_c, s, ω, ω_0, A: complex slowness, normal slowness, angular frequency, reference angular frequency, and the attenuation factor $A = 1/Q$ as the inverse of the Q value, respectively. The modular nature of FWMod facilitates the integration of the Q-effect by simply adapting the propagation operator (Safari and Verschuur, 2023). The involved phase shift operators in the wavenumber-frequency domain for 2D after including attenuation are as follows:

$$W(k_x, \omega) = e^{-jk_z\Delta z};\ k_z = \sqrt{\omega^2 {s_c}^2 - k_x^2}\,, \tag{2}$$

with Δz the extrapolation distance. For application in the 2D space-frequency domain, this propagation operator is inverse Fourier transformed from wavenumber to the lateral coordinate under the assumption of a locally invariant medium. The quality factor (Q) updating procedure effectively constitutes a tomographic problem where we combine wavefields that travel in the same direction. A linear relationship between propagation operators and the attenuation model can be derived by analyzing their perturbations. By adapting the method outlined by (Safari and Verschuur, 2024), a linearized form of the equation in the wavenumber-frequency domain is obtained:

$$\Delta W = W_{new} - W_{old} \approx \left[\frac{\partial W}{\partial A}\right]_{old} \Delta A \tag{3}$$

$$\Delta W = -\frac{i\omega^2 s^2}{k_z}\left(\left(1 - \frac{A}{\pi}\ln(\omega/\omega_0)\right)\left(1 + \frac{iA}{2}\right)^2\left(\frac{\ln(\omega/\omega_0)}{\pi}\right) + \left(\frac{i}{2}\right)\left(1 + \frac{iA}{2}\right)\left(1 - \frac{A}{\pi}\ln(\omega/\omega_0)\right)^2\right) W_{old}\Delta A \Delta z\,,$$

where W_{new} represents the operator associated with an updated attenuation model, while W_{old} corresponds to the operator in the current attenuation model, and ΔA denotes the attenuation update. This formulation builds on the linearization approach for phase-shift operators, as detailed by Shen et al. (2018), but includes all potentially contributing terms without excluding those deemed to have minor contributions. The resulting expression can be inverse Fourier transformed into the space domain, enabling the calculation of spatially varying gradients from propagation operators.

The foundation of our method is an inversion algorithm that iteratively updates the subsurface reflectivity model to align with the actual seismic data. This is achieved using a gradient descent method, where the residual is back-propagated to each depth level during each iteration and combined with the forward-modeled source field. Depending on the imaging condition applied after back-propagation, either the reflectivity or attenuation is updated. The step length for the gradient update, influencing attenuation or reflectivity, is determined by computing a forward model of the gradient's linearized effect on the recorded wavefield and comparing it with the residual data.

Updating the quality factor (Q) is challenging due to the crosstalk between reflectivity and Q, necessitating constraints for accurate estimation. Traditional methods for addressing the crosstalk, such as Hessian-based approaches or deep learning models, are effective but computationally expensive. To overcome these challenges, we applied a Random Forest (RF) regression to constrain the iterative estimation of Q by linking it to other parameters. RF is a machine-learning technique that combines multiple decision trees to improve accuracy while avoiding overfitting (Breiman, 2001). This method is computationally efficient and well-suited to capturing complex nonlinear relationships. In our approach, we used velocity and depth as predictors for RF because seismic attenuation is known to be linked to velocity dispersion (Aki and Richards, 2002). By incorporating these physical relationships into the RF model, we ensured that the Q-estimation was not only computationally efficient but also physically consistent. The RF model was applied at each iteration to refine the Q-model, providing a cost-effective and reliable solution for Q-estimation.

Numerical tests

To evaluate the performance of our enhanced Full Wavefield Migration (FWM) method, we conducted a synthetic test using a model with two rectangular anomalies characterized by distinct attenuation properties. The background medium was modeled as non-attenuative, except for a high-attenuation anomaly (Q = 20) in the top-right corner and a moderate-attenuation anomaly (Q = 50). Two reflectors were included beneath these anomalies. The setup used a frequency range of 5–60 Hz, with a maximum data offset of 3000 m and a depth of 1400 m. Sources and receivers were evenly distributed along the surface.

Four scenarios were analyzed in this test. In the first scenario, traditional FWM was applied, assuming the medium was non-attenuative, with the Q model shown in Figure 1b. In the second scenario, the correct Q model, shown in Figure 1d, was provided as prior knowledge to enable accurate reflectivity estimation of our QFWM method. In the third scenario, both Q and reflectivity were jointly estimated using gradient descent during the iterative process without using any constraint. Finally, in the fourth scenario, Q and reflectivity were estimated jointly, as in scenario 3, but with Random Forest constraints applied to further improve parameter accuracy by mitigating cross-talk between Q and reflectivity.

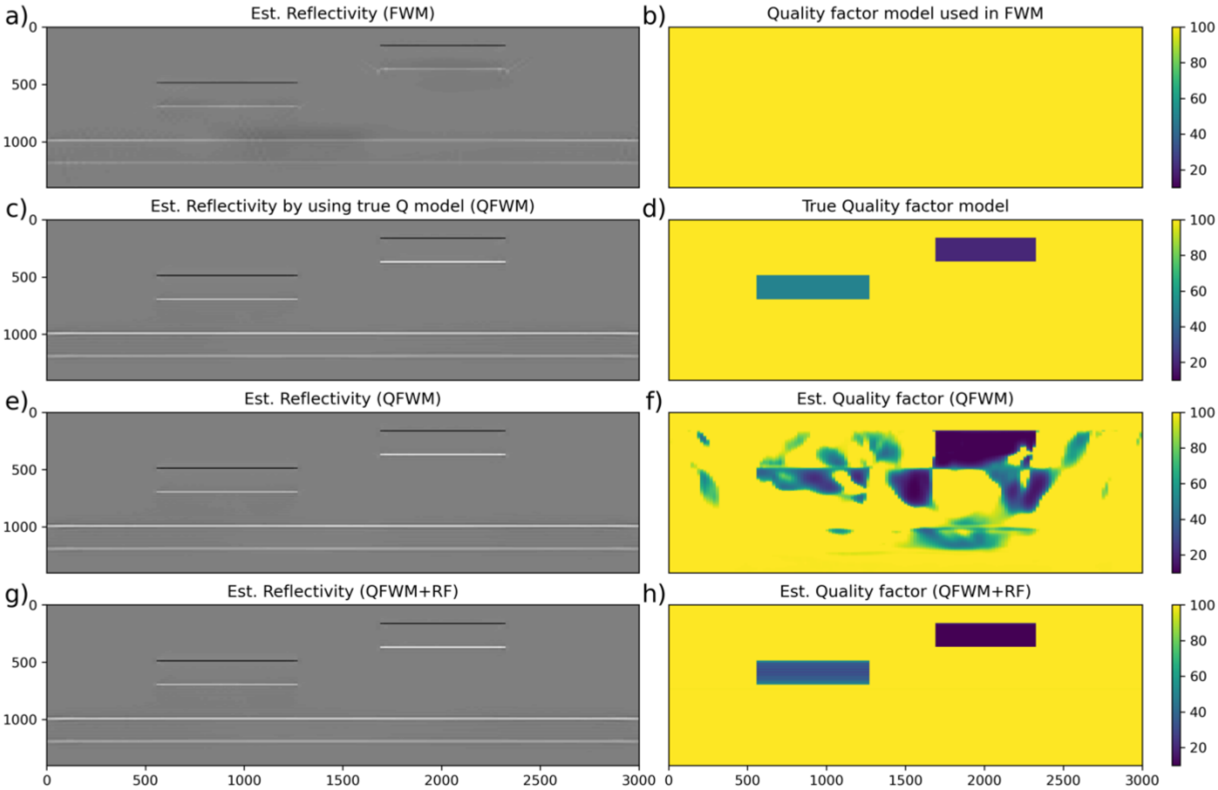

***Figure 1**: Reflectivity and Q Estimation Across FWM and QFWM Scenarios. a) Reflectivity by FWM using the high Q model (non-attenuative). b) High Q model used in FWM. c) Reflectivity by QFWM with the correct Q model. d) True Q model. e) Reflectivity by QFWM (unconstrained). f) Q by QFWM (unconstrained). g) Reflectivity by QFWM with Random Forest constraints. h) Q by QFWM with Random Forest constraints.*

The results are summarized in Figure 1. The standard FWM, as shown in Figure 1a and based on the Q model assumption in Figure 1b, fails to account for attenuation effects, leading to reduced resolution and inaccuracies in reflectivity estimation. In contrast, Figure 1c demonstrates the improved reflectivity estimation achieved with QFWM, which used the correct Q model shown in Figure 1d. The use of the correct Q model eliminates the attenuation imprints on the reflectors, resulting in a more accurate reflectivity estimation. Figures 1e and 1f present the results of QFWM when both reflectivity and Q are jointly estimated without constraints, showing that the Q model is sufficiently accurate to produce high-resolution reflectivity. Finally, Figures 1g and 1h illustrate the results of the fourth scenario, where Random Forest constraints were applied in addition to the joint estimation process of the third scenario. These constraints further enhance the accuracy of the Q model, reduce cross-talk, and improve the reliability of the reflectivity estimation compared to the unconstrained case.

The wavefield residuals from all scenarios are presented in Figure 2, illustrating a significant reduction in residuals when Q is included in the FWM process. Estimating Q rather than using the correct Q model decreases the residuals but not to the same extent as when the correct Q model is provided. However, applying Random Forest constraints further reduces the residuals, achieving results comparable to those obtained with the correct Q model. These findings confirm the effectiveness of our QFWM method in enhancing the accuracy of both reflectivity and Q estimation while ensuring a better match between the modeled and observed data.

Conclusions

Attenuation has become a crucial factor in imaging real seismic data. For the Full Wavefield Migration (FWM) process, this integration can be seamlessly implemented within the forward modeling framework, which is constructed using distinct propagation and scattering operators. The propagation operator, employing laterally varying phase shifts, can be easily adapted to include Q-effects. We proposed an approach that utilizes full-waveform matching for accurate Q-estimation based on residual data and compensates for it during the migration process. Additionally, applying constraints on the estimated Q model using a Random Forest regression scheme significantly enhances Q estimation and improves the precise localization of highly attenuative zones. We have demonstrated that the Random Forest method offers a cost-effective alternative to more computationally intensive approaches, such as Hessian-based methods and deep learning frameworks, commonly employed to mitigate cross-talk, thereby highlighting its practical utility. Numerical examples demonstrated that the proposed method accurately retrieves both reflectivity and attenuation models. In this work, we assume a reliable velocity model to focus on improving the accuracy of reflectivity and attenuation estimation. This step is essential for ensuring the robustness of the method before progressing toward a comprehensive multiparameter inversion framework capable of simultaneously estimating reflectivity, velocity, and attenuation models. The work presented here provides a necessary foundation for achieving this ultimate goal, paving the way for a more stable and accurate approach to multiparameter seismic imaging.

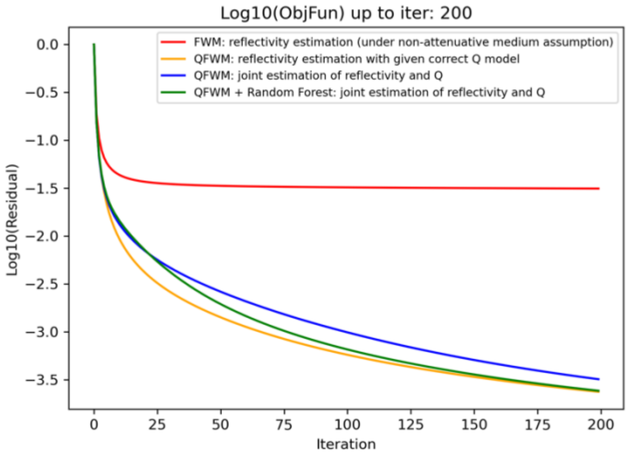

Figure 2*: Comparative analysis of the wavefield residual.*

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