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Layered Q-Factor Estimation via Convolutional Seismic Modeling

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Abstract Summary

This work presents a method for estimating the seismic quality factor (Q) from surface reflection data by formulating an inverse problem based on the convolutional model. The method directly parameterizes the model as a function of a spatially varying Q-factor and seeks the values that minimize the mean square error between the observed seismic trace and the synthetic trace generated by the model. Attenuation is incorporated into the inversion using the Kolsky-Futterman formulation. The scenario assumes known source and reflectivity functions, with the Q-factor varying across geological layers but remaining constant within each layer. The inversion is performed using the Adaptive Moment Estimation (Adam) optimizer, and the initial results show that the proposed method accurately estimates the Q-factor and reconstructs the seismic response.

Introduction

To generate high-resolution seismic images, it is essential to accurately account for both energy dissipation and velocity dispersion effects. One common strategy is the application of wave-propagation reversal techniques, such as inverse Q filtering, which depend on reliable estimates of the subsurface Q-factor. Although many existing methods rely on Vertical Seismic Profile (VSP) data (Cheng and Margrave, 2012), estimating Q from surface reflection data is often more practical and broadly applicable. Several techniques have been proposed for this purpose, including enhanced log spectral ratio methods (Liu et al., 2022), interferometric approaches using VSP data (Matsushima et al., 2015), and time-frequency analysis techniques (Liu et al., 2024).

This work presents a novel method for estimating the Q-factor from surface reflection data by formulating an inverse problem based on the convolutional model (Takahata et al., 2012). Unlike conventional approaches, the proposed method explicitly parameterizes the convolutional model as a function of the spatially varying Q-factor and adjusts its values to match the synthetic trace to the observed data. A key strength of this approach is its flexibility: different attenuation models can be seamlessly incorporated into the same inversion framework. The inversion is performed by minimizing the mean square error between the observed and estimated traces using the Adaptive Moment Estimation (Adam) optimizer. To assess the method's performance, we apply it to synthetic data generated using the frequency-independent Q-model proposed by Kjartansson, as described by Ursin and Toverud (2002), assuming that Q varies across geological layers but remains constant within each layer. For the inversion, we adopt the Kolsky-Futterman model (Wang, 2006), enabling us to explore the effects of model mismatch in the estimation process.

Theory and Method

According to Ergun (2019), seismic data $x(t)$ can be described as the convolution of the source wavelet $s(t)$, a non-stationary function $a(t,\tau)$ modeling attenuation, and the reflectivity series $r(t)$:

$$x(t) = s(t) * a(t,\tau) \odot r(t), \tag{1}$$

where $*$ and $\odot$ denote stationary and non-stationary convolution, respectively, and τ is the travel time in the medium. The discrete form of Eq. 1 is:

$$\mathbf{x} = \mathbf{SAr}, \tag{2}$$

where $\mathbf{r}$ is a vector of length N_r built from the discretized reflectivity series; $\mathbf{S}$ is a $(N_r + N_s - 1) \times N_r$ Toeplitz matrix formed by shifting the discretized wavelet $s(t)$ along the matrix columns; and $\mathbf{A}$ is the $N_r \times N_r$ attenuation matrix, which is a function of the Q-factor.

To construct $\mathbf{A}$, two assumptions are made: the medium is linear, and the depth axis is divided into sub-layers of length $\Delta z_n = v_n(\omega_r)\Delta\tau$, where $v_n(\omega_r)$ is the phase velocity in the n-th layer and $\Delta\tau$ is the constant travel-time step. Under these assumptions, the wavefield is represented as a superposition of plane waves at fixed angular frequency ω (Futterman, 1962), which leads to an inverse Fourier transform operation. Thus, the amplitude at time t in the n-th layer is:

$$u_n(t) = \mathcal{F}^{-1}\left\{ S(\omega) \exp\left[-i\Delta\tau \sum_{j=1}^{n} k_j(\omega) v_j(\omega_r) \right] \right\}. \tag{3}$$

where $S(\omega)$ is the spectrum of $s(t)$, and $k_j(\omega)$ is the wavenumber in the j-th layer. Using the convolution property of the Fourier transform, this can be rewritten as:

$$u_n(t) = s(t) * a_n(t), \tag{4}$$

with:

$$a_n(t) = \mathcal{F}^{-1}\left\{ \exp\left[-i\Delta\tau \sum_{j=1}^{n} k_j(\omega) v_j(\omega_r) \right] \right\}. \tag{5}$$

This function describes how the source wavelet $s(t)$ is attenuated upon reaching the n-th layer. To account for the attenuation across all layers, the attenuation matrix is defined as follows:

$$\mathbf{A} = \begin{bmatrix} \mathbf{a}_0 & \mathbf{a}_1 & \cdots & \mathbf{a}_{N_r-1} \end{bmatrix}, \tag{6}$$

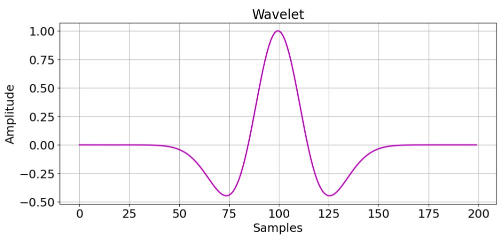
where each column $\mathbf{a}_n$ is a discretization of Eq. 5 for the corresponding layer n. The choice of the Q-model is defined through expressions for $k_j(\omega)$, which control the attenuation behavior (Wang, 2006). The proposed Q-factor estimation method parameterizes $\mathbf{A}$ using a vector $\mathbf{q}$ of length N_r, where each element corresponds to the Q-factor of a layer. A synthetic trace is generated using Eq. 2, and $\mathbf{q}$ is optimized to minimize the squared ℓ_2-norm between the estimated and observed traces:

$$\min_{\mathbf{q}} \frac{1}{2} \left\| \mathbf{SAr} - \mathbf{x_{obs}} \right\|_2^2. \tag{7}$$

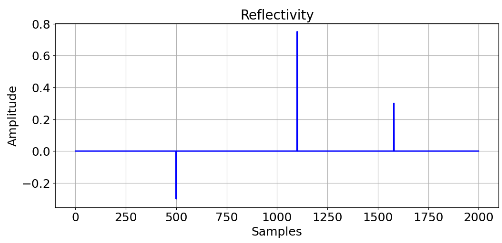
Results

To evaluate the proposed Q-factor estimation algorithm, a synthetic seismic trace $\mathbf{x_{obs}}$ was generated using the non-stationary convolutional model in Eq. 2. The matrix $\mathbf{S}$ and the reflectivity vector $\mathbf{r}$ were constructed using the data shown in Figures 1a and 1b. The attenuation matrix was constructed using the wavenumber defined by the Kjartansson model for seismic attenuation, which considers the Q-factor to be independent of frequency (Ursin and Toverud, 2002). The true Q-factor profile $\mathbf{q_{obs}}$ is shown in Figure 2a, and the resulting seismic trace $\mathbf{x_{obs}}$ is shown in Figure 2b.

For the estimation, $\mathbf{S}$ and $\mathbf{r}$ are assumed to be known, making the Q-profile the only unknown. The Kolsky-Futterman model (Kolsky, 1964) was selected for inversion due to its broad compatibility with other attenuation models (Ursin and Toverud, 2002). The initial guess $\mathbf{q_0}$ is uniformly set to 100, representing a low-attenuation medium with no layer-to-layer variation. The estimated profile $\hat{\mathbf{q}}$ after 150 iterations is shown in Figure 2a; the resulting traces $\mathbf{x_0}$, $\hat{\mathbf{x}}$, and $\mathbf{x_{obs}}$ are displayed in Figure 2b; and the cost function evolution is depicted in Figure 2c, where most of the error reduction occurs within the first 50 iterations. The curve then gradually stabilizes, indicating that the optimizer converges to a near-optimal solution with minimal improvement beyond iteration 100.

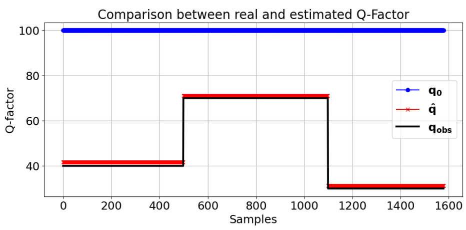


(a) Source wavelet.

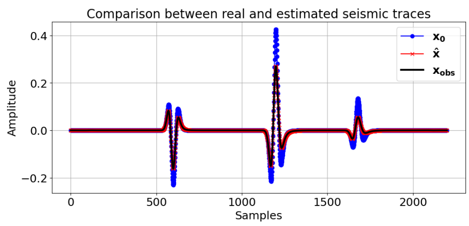


(b) Reflectivity function.

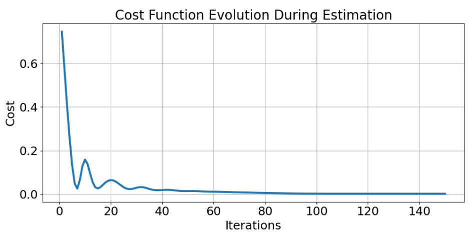
Figure 1: Parameters used to generate the synthetic seismic data.



(a) Estimated Q-factor profile.



(b) Reconstructed seismic trace.



(c) Cost function evolution through iterations.

Figure 2: Results of the Q-factor estimation procedure.

Conclusions

This work proposed a flexible method for estimating the seismic quality factor Q from surface reflection data, formulated as an inverse problem based on the convolutional model. The method was applied to a single synthetic seismic trace, assuming known reflectivity and source wavelet. The inversion adopted the Kolsky-Futterman model, while the data were generated using the Kjartansson model, which is known to be highly compatible with Kolsky-Futterman.

The results demonstrate that the proposed approach accurately reconstructs the seismic trace and provides reliable estimates of the layered Q-profile, even in the presence of moderate model mismatch. The estimated Q values closely follow the true layerwise profile, confirming the method's ability to capture attenuation variations across the medium.

These findings reinforce both the effectiveness and the model-dependence of Q-factor estimation, underscoring the importance of interpreting Q within the context of the assumed attenuation model. As future work, we plan to extend the method to blind deconvolution, allowing for the simultaneous estimation of Q, the source wavelet, and the reflectivity. Other goals include investigating different attenuation models for both data generation and estimation, in order to better understand the impact of model mismatch on the inversion results, and performing tests under more realistic conditions.

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