Systematic bandwidth picking for the spectral ratio method

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ABSTRACT

We use the spectral ratio method to estimate the effect of anelastic attenuation. The proper bandwidth over which to use the method is not constant throughout the entire image of the subsurface. Hand picking the correct bandwidth at every location would be prohibitive for a large 2D, let alone 3D image. Herein, various techniques are explored to systematically identify the upper and lower frequency bounds in order to improve performance of the spectral ratio method over large data sets. These techniques are evaluated with a visual metric to asses the accuracy of their bandwidth picks.

INTRODUCTION

Anelastic attenuation is represented by the Q factor in reflection seismology. A good estimate of the Q factor is useful for reflection data processing and rock property prediction. For example, processing methods, such as migration, Q filtering, and deconvolution that account for attenuation can produce higher quality images than methods which ignore it. Further, attenuation estimates can reveal information about porosity, permeability, and fluid saturation useful for reservoir characterization (Best et al., 1994).

There are numerous techniques that attempt to accurately predict the Q factor within a seismic image. The spectral ratio method is regarded as one of the more robust techniques (Tonn, 1991). A benefit of the spectral ratio method is that it can be performed over a limited range of frequencies that are signal dominated, hence disregarding noise or artifact dominated parts of the spectrum. While this makes the technique more versatile, it also implies the signal dominated bandwidth of the spectra must be chosen beforehand. Moreover, the proper bandwidth is not constant throughout the seismic image, implying it must be independently chosen at every location. Manually picking this proper bandwidth at every location would be extremely time consuming.

If a systematic technique could be developed to accurately pick the signal dominated bandwidth, the speed at which the spectral ratio method could be performed over an entire seismic image would increase dramatically. Consequently, the speed at which the Q factor, the output of the spectral ratio method, could be found at every point in a model would also increase. The focus of this study is picking the proper bandwidth for the spectral ration method.

I considered many techniques to pick the correct bandwidth for the spectral ratio method. It was logical to begin with the simplest methods and progress towards more complex ones. Those tested here:

1. use a constant, narrow bandwidth that might represent signal dominated frequencies at all locations,
2. fix the lower frequency bound and linearly decrease the upper bound with depth,
3. center the bandwidth around the peak frequency.

I also discuss other techniques that may perform better than those tested in this report.

SPECTRAL RATIO METHOD

The spectral ratio method can be used to determine the Q effect over some discretization of a seismic image by comparing incident and outgoing waves. Take some outgoing wave, $R(f)$, which is the result of some incident wave, $S(f)$, and the attenuating medium response $GH(f)$:

$$R(f) = GH(f)S(f) \tag{1}$$

where f is frequency and G represents the geometrical spreading, instrument response, source and receiver coupling, radiation pattern, and reflection/transmission coefficients. $H(f)$ includes the attenuation effect on amplitude and was shown by Ward and Toksz (1971) to be expandable to

$$H(f) = \mathrm{e}^{-f \int_{ray} \frac{\pi}{Qv}}, \tag{2}$$

where v is the wave velocity. Substituting $H(f)$ into equation 1 gives

$$R(f) = G\mathrm{e}^{-f \int_{ray} \frac{\pi}{Qv}} S(f). \tag{3}$$

With some manipulation, equation 3 becomes:

$$ln[R(f)/S(f)] = (\int_{ray} \frac{\pi}{Qv})f - ln(G). \tag{4}$$

This reveals that the relation between $R(f)$ and $S(f)$ is linear with respect to frequency following

$$y(f) = mf + b, \tag{5}$$

where

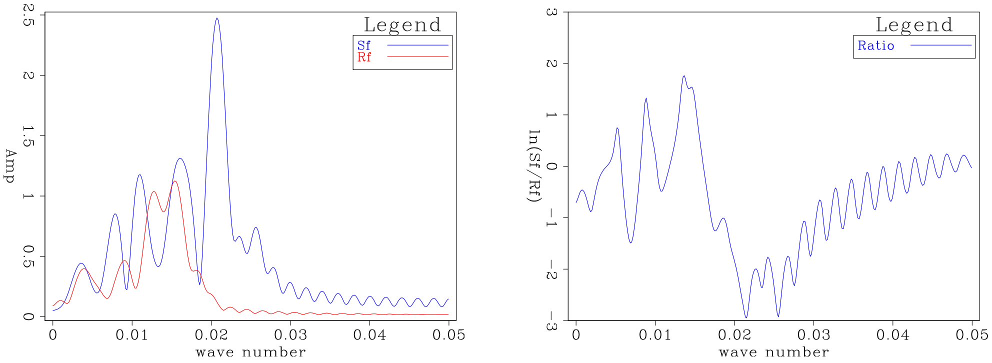
$$y(f) = ln[R(f)/S(f)], \tag{6}$$

$$m = \left(\int_{ray} \frac{\pi}{Qv}\right), \tag{7}$$

$$b = -ln(G). \tag{8}$$

Therefore, Q can be found using the slope of the line representing the log of the ratio between the input spectrum, $S(f)$, and the output spectrum, $R(f)$. Notice that the b term can be ignored which means this method is not affected by G and its dependencies.

In practice, the seismic image is discretized into spectrum windows. Each window is of the order of tens of meters wide and hundreds of meters tall. Windows overlap to ensure spectra are not dominated by local reflectivity. To calculate Q at each window, the spectrum is treated as the outgoing $R(f)$ and is divided by some input spectrum $S(f)$. The input spectrum $S(f)$ does not necessarily need to be the source spectrum, but can be some spectrum from a non-attenuated window. I will call this the reference window. The log of this ratio is calculated and the line of best fit is found. Using Equation 7, Q can be found from the slope of this line. Figure 1 illustrates an example of $R(f)$, $S(f)$, and their log ratio.



(a) (b)

Figure 1: a) Spectra of some window of interest and a reference window, b) log ratio of the reference spectra divided by the window of interest. [**ER**]

An added advantage to the spectral ratio method is that is can be applied over a limited range of frequencies to avoid those dominated by noise. As seen in Figure 1, data above wavenumber 0.03 represent noise and rather than signal. If linear regression is performed over all wave numbers, the resulting line and its slope will be largely affected by the noise dominated region. The noise can be avoided by evaluating the line only over the signal dominated wavenumbers. Picking the correct frequencies to evaluate is the purpose of this investigation.

DATA

The data used in this analysis is Dolphin Geophysical's multi-client field data acquired in the North Sea. There are significant velocity and attenuation challenges caused by a salt body with two peaks. As interpreted by Dolphin, a gas chimney is present above one of the salt peaks and a channel above the other. The gas chimney forms a migration pathway for gas to leak and accumulate at shallow depths above the salt. The shallow gas gives rise to strong attenuation and low interval velocity. The channel also has low velocities and provides strong attenuation. These regions of strong attenuation, and therefore significant Q effects, make the dataset ideal for testing the spectral ratio method.

As previously mentioned, the seismic image will be discretized into spectra windows. The window size used in this study is 500 m in the z direction and 125 m in the x direction. The spectrum at each window will be the total spectrum from a window of this size centered at the window's location in the subsurface.

BANDWIDTH PICKING TECHNIQUES

Herein I present the various methods tested for choosing the correct bandwidth over which to perform the spectral ratio method.

Constant bandwidth

The most simple technique is to use a constant bandwidth for all windows. A bandwidth should be chosen that could reasonably represent the frequencies dominated by signal for all depths and locations in the subsurface.

Linearly shrinking bandwidth

With this technique the lower frequency bound is fixed and the upper bound decreases linearly with depth. Since higher frequencies are expected to naturally attenuate with depth, it follows that the bandwidth dominated by signal should also shrink with depth. I implement two variations of this method. In the first, I fix the lower bound at wavenumber 0.0 and linearly move the upper bound from wavenumber 0.04 to 0.02. In the second, I fix the lower bound at 0.005 and linearly move the upper bound from wavenumber 0.04 to 0.02. I vary the lower bound in an attempt to avoid low frequency noise.

Center around peak

The frequency with the largest amplitude most likely represents the location with the strongest signal. By centering the bandwidth around this region, it is reasonable to assume it represents a bandwidth dominated by signal. This bandwidth should be wide enough to capture enough frequencies to produce a spectral method result representative of the signal dominated region, but narrow enough to avoid noise dominated frequencies. Here, I used a width of 0.015 wavenumbers centered around the peak frequency.

RESULTS

A metric is required to compare the results of each picking method. I use a visual metric focusing on the slope of the log ratio used in the spectral ratio method.

At nine locations over a 2D slice of the Dolphin dataset, presented in Figure 2, the bandwidth dominated by signal was chosen manually. The slope was found from the log ratio of the picked window and a reference window. This will be the control slope. We can see that the windows at the center of Figure 2 are non-attenuated. These were used as the reference windows. At the nine locations, each picking method selected a particular bandwidth. The slope was then found over the bandwidth picked by each method. By visually comparing the manually picked slopes with the slopes picked by each method, the accuracy of each technique can be evaluated.

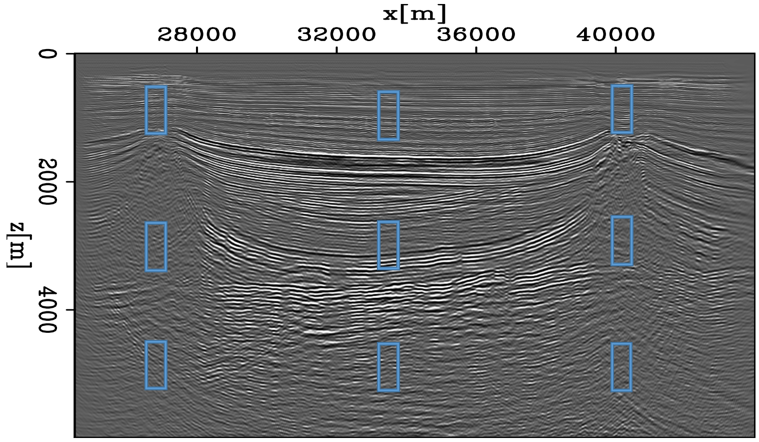
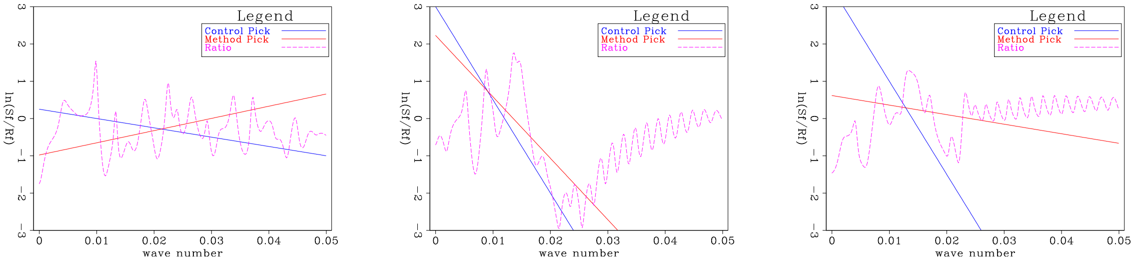


Figure 2: Location of nine visual metric locations. Size of windows not representative of actual window size. [**NR**]

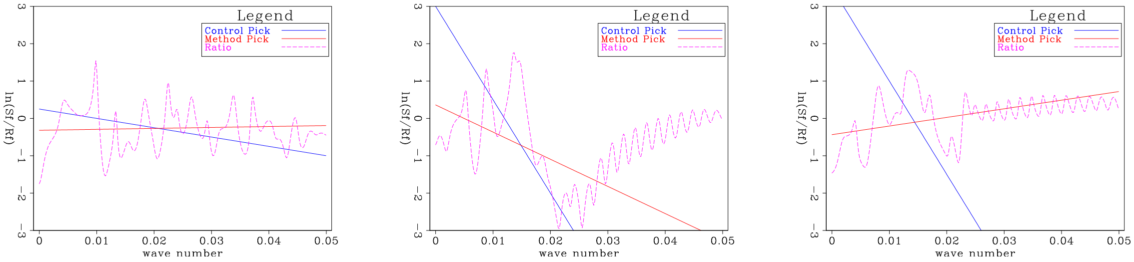
Slope results

To illustrate the varying slope results for each technique, I chose three windows to analyze. The windows are located at 40,000 meters, as seen in Figure 2, with depths of 1000, 3000, and 5000 meters. These three windows were chosen because they represent regions in the subsurface with varying amounts of noise. Figures 3, 4, 5, and 6 show results for each of these windows. In each graph, there are three lines. The dashed, pink line is the log of the ratio between the reference window and the current window. Again, the slopes are calculated by linear regression over some bandwidth of this log ratio line. The solid blue line is the control slope pick. The solid red line is the slope picked by one of the designed techniques.



(a) (b) (c)

Figure 3: Log ratio (dashed pink), control slope pick (solid blue), and constant bandwidth method slope pick (solid red) at x=40000 m and, (a) z=1000 m, (b) z=3000 m, (c) z=5000 m [**ER**]



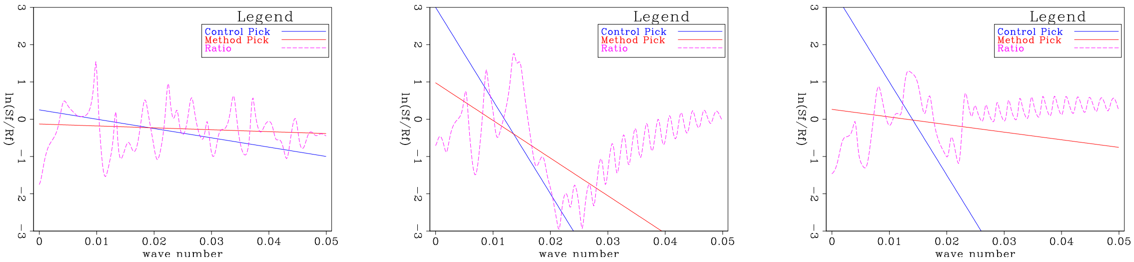
(a) (b) (c)

Figure 4: Log ratio (dashed pink), control slope pick (solid blue), and linearly shrinking bandwidth (min=wavenumber 0.00) slope pick (solid red) at x=40000 m and, (a) z=1000 m, (b) z=3000 m, (c) z=5000 m [**ER**]

While the metric comparing slope picks is useful for analyzing accuracy at individual windows, it does not reveal how a technique performs throughout the entire image. To gain insight into the big picture results, the slopes were calculated at every window using each technique. These slope panels are displayed in Figure 7. A clip of 150 was applied to each panel.

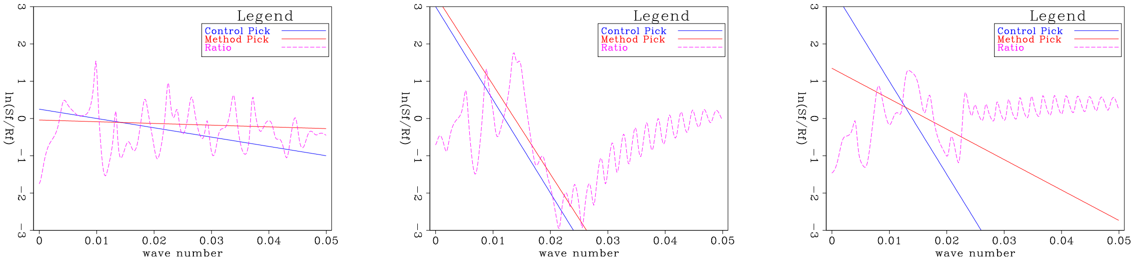
DISCUSSION

Figure 6 shows the technique centered around the peak frequency best matched the control picks. This is a reasonable result since it is the only method that actually considers the spectrum of the current window. Other methods blindly choose bandwidths without dynamically considering where the signal is most dominant. Still, each method had trouble matching the control at large depths and often at shallow depths. As currently implemented, none of the methods can be considered accurate enough fot systematically picking the correct bandwidth over which to perform the spectral ratio method.



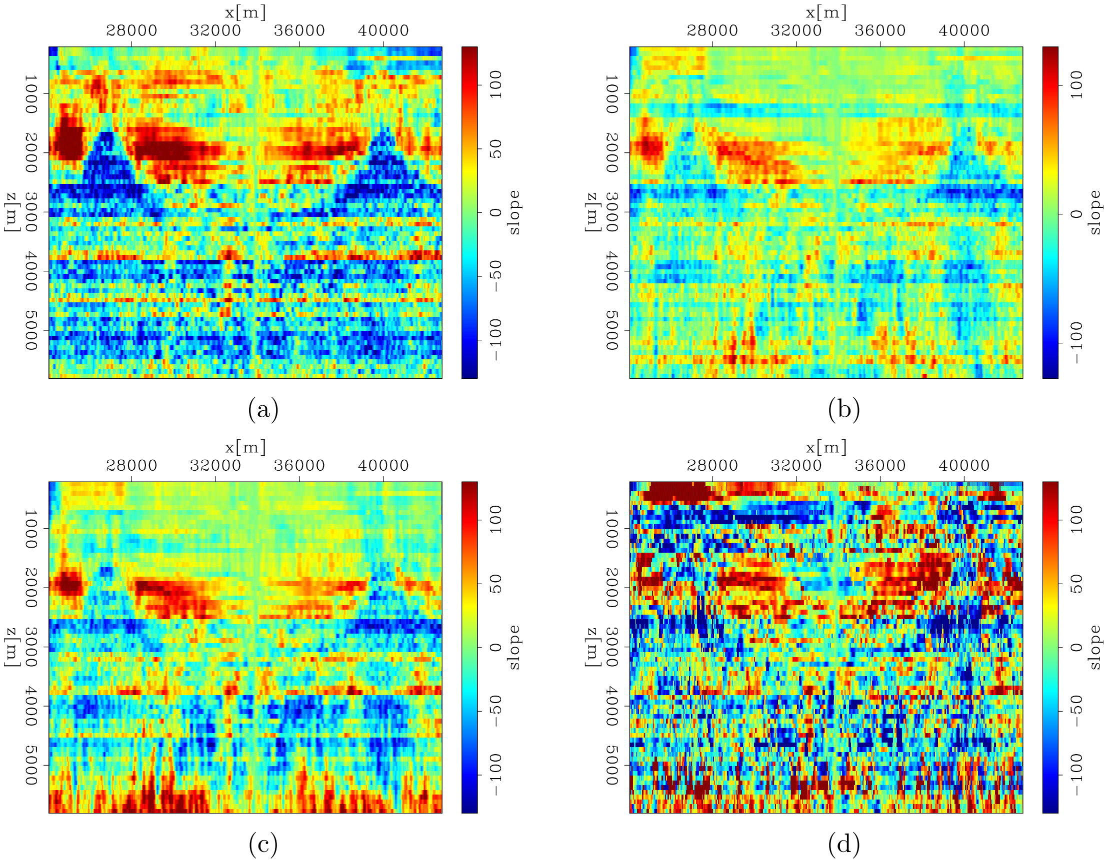
(a) (b) (c)

Figure 5: Log ratio (dashed pink), control slope pick (solid blue), and linearly shrinking bandwidth (min=wavenumber 0.005) slope pick (solid red) at x=40000 m and, (a) z=1000 m, (b) z=3000 m, (c) z=5000 m [**ER**]



(a) (b) (c)

Figure 6: Log ratio (dashed pink), control slope pick (solid blue), and bandwidth centered around peak slope pick at x=40000 m and, (a) z=1000 m, (b) z=3000 m, (c) z=5000 m [**ER**]



(a) (b) (c) (d)

Figure 7: Slope values at every window for (a) constant bandwidth method, (b) linearly shrinking bandwidth (min= wavenumber 0.0), (c) linearly shrinking bandwidth (min= wavenumber 0.005), (d) bandwidth centering around peak frequency [**ER**]

While the full slope panels in Figure 7 were not the main metric used to determine viability, they do provide unique insight. Primarily, these panels reveal a promising proof of concept. Each contains a slope trend that outlines the salt bodies beneath the shallow Q anomalies seen in the original data image. These slope trends almost appear as lenses beneath the Q anomalies. Since we would expect higher attenuation under these anomalies, it is promising that the techniques are finding slope trends that are directly related to lower Q values. Furthermore, the large positive slopes seen near these lenses are caused by the large size of each window. Indeed, the spectrum at each window is actually an average of a few traces 500 meters in length. This implies that some windows interact with regions affected by the shallow Q anomalies when they are actually located outside the lensing region. This interaction causes an anomalous log ratio result leading to a positive slope outcome. Therefore, these large positive anomalies are not caused by the bandwidth picking methods but by the large window size.

FUTURE WORK WITH NEW TECHNIQUES

A numeric metric should be created to determine the viability of each bandwidth picking method. One possibility is to find the mean square error (MSE) between the control slopes and the slopes found by each technique. This would quantify how far the results are from the control.

A more sophisticated bandwidth picking technique could be developed using machine learning. I can see two possible approaches. The first would use regression methods based on control bandwidth picks to find parametric estimations of the lower and upper frequency values. The second would be a clustering method analyzing various parameters such as signal-to-noise, amplitude, average frequency, or spikiness.

Finally, the window size used to discretize the image's spectrum could be altered. There exists an optimal size that eliminates local reflectivity but avoids issues on the borders of large Q anomalies.

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