Velocity analysis in the data domain – overview and prospects

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SUMMARY

Automatic versions of migration velocity analysis provide velocity background models that can serve as a starting point for migration or least-squares inversion. When dealing with primary reflections, current methods perform well. They tend to break down, however, when strong multiples are present. This is due to the single scattering approximation that underlies most migration algorithms. When multiples are interpreted as primaries, they may end up at the wrong depth with the wrong apparent velocity. In the data-domain, it should in principle be possible to match observed with predicted multiples and use them for velocity estimation. We present a method for performing the velocity analysis in the data domain and include tests on multiple-free synthetic data and on real data, using the convolutional model to model the data. We also outline ideas on how the method is expected to behave in the presence of multiples.

Introduction

In waveform inversion, one uses the full wave equation to model the data and tries to find the model parameters, for instance, velocity and density, that produce synthetic data that best fit the measured data in a least-squares sense (Tarantola and Valette, 1982). While this approach allows for the incorporation of more realistic physics, there are some drawbacks. The absence of low frequencies in the data makes it usually very hard to obtain information about the slowly varying components of the velocity model beyond the depth reached by diving waves. In the shallower regime, reflected and diving waves provide independent information about the reflectivity and the background model, respectively. We therefore can recover both from the data (Pratt *et al.*, 1996). In the deeper regime, only reflection data are available and there exists an ambiguity between depth and velocity to explain the traveltime of an event in the data, leading to local minima in the least-squares error. Usually, Migration Velocity Analysis (MVA) is used to update the background velocity model in this regime. However, most migration algorithms are based on single-scattering and one-way approximations and lack the physical fidelity of waveform inversion. Therefore, we seek a method to perform the velocity analysis in the data domain. This will allows us to use the full wave-equation to model the data. The main idea is to generate new data from a migrated image and compare this to the measured data in some sense. The ideas are first tested using the convolutional model to model the data.

Migration velocity analysis

Migration velocity analysis is based on optimizing the migration image. Suitable measures are semblance or differential semblance (Symes and Carazzone, 1991; Mulder and ten Kroode, 2002). For shot-based wave propagation algorithms, offset at depth is a useful alternative to source-receiver offset (Shen *et al.*, 2003). Figure 1 shows an example for seismic data obtained with the convolutional model and NMO traveltimes in a horizontally layered medium. The first panel from the left shows the data with added free-surface multiples. The second panel displays the image gather as a function of offset-at-depth Δh and two-way traveltime, which is used to parametrize depth in the convolutional model. The image is based on a subsurface model with too low velocities. The third panel shows the image for the true velocity and the fourth, right-most one, for a velocity that is too high. The primaries focus at zero offset Δh in the correct model. Events that do not focus appear as hyperbolas. Because we have a one-sided acquisition with receivers to the right of the sources, we only obtain a part of the hyperbola. The algorithm for velocity analysis tries to concentrate energy at zero offset-at-depth Δh by penalizing contributions at larger values of Δh. It is clear that this method will provide inaccurate results in the presence of multiples. In this case, the free-surface multiples have a lower effective velocity than the primaries, as is typical in a marine setting. This means that the algorithm will provide velocities that are too low. In the third panel from the left in Figure 1, we see that all the multiple energy lies at negative Δh. A penalization scheme that acts stronger for positive Δh than for negative Δh will make the method less sensitive to multiples. However, in the presence of velocity inversion and strong interbed multiples, this cure will not help.

Data-domain velocity analysis

The data $p(t,x)$ satisfy

$$\mathcal{L}[m]u(t,x,z) = f(t,x,z), \tag{1}$$

$$p(t,x) = u(t,x,0). \tag{2}$$

where $\mathcal{L}[m]$ is the appropriate wave operator, which depends on the squared slowness $m(z) = 1/v(z)^2$. The idea of data-domain velocity analysis is the following. First, we obtain an image (reflectivity) for the current background model and subsequently generate data for the velocity model composed of the reflectivity and background model. These predicted data are then compared to the observed data to obtain an update of the background model. We denote the smooth background model as m_0 and the corresponding migrated image as $r[m_0]$. The predicted data are then obtained by solving equation 2 for $m = m_0 + r[m_0]$. The events in this predicted data set have the same zero-offset traveltimes as the measured data, but a different moveout, depending on the background model.

MBTT

Migration Based Traveltime Tomography compares the measured and predicted data in a least-squares sense. Chavent *et al.* (1994) showed that this method is more successful in updating the background model than classical least-squares inversion. However, if the initial model is too far from the true model, the method may still end up in a local minimum. Conceptually, the method can be compared to the stackpower criterion that updates the velocity model by maximizing the amplitude of the migrated image.

Data correlation

Another data-domain approach is based on the correlation of the predicted and measured data (van Leeuwen and Mulder, 2007). This correlation will 'focus' when the moveout (and hence the velocity models) of predicted and measured data is the same. Figure 2 shows an example. The amount of focusing is measured with a weighted norm and the velocity model can be updated to optimize this norm.

Example

We demonstrate here that we can obtain a good NMO velocity model with the data-correlation approach, starting from a constant initial velocity model. The reflectivity was obtained by stacking the NMO corrected data for the initial velocity model and data were modeled with the convolutional model. The velocity model, which was obtained by optimizing the amount of focusing of the data correlation, flattens the events after NMO correction. The results are depicted in figure 3.

Multiples

By performing the velocity analysis in the data domain, multiples in the data can be matched with modeled multiples. However, the multiples can only be modeled correctly if the reflectivity is correct. Obtaining the correct reflectivity in the presence of multiples can be problematic. By alternately updating the reflectivity and the velocity model this problem might be circumvented. Figure 4 shows a simple example on synthetic data.

Discussion

The data-correlation approach can provide a good NMO velocity model for primary only data. First tests with multiples on synthetic data seem hopeful. Obtaining a good estimate of the reflectivity is crucial in this approach. To obtain good results with real data the multiples will have to modeled correctly. Even when this can be achieved, problems are expected when the multiples contain more energy than the primaries. In this case, the data-correlation approach may have difficulties focusing the weaker primaries in the presence of strong, already focused multiples. Also, the data-correlation is only sensitive to moveout differences, and hence only the *effective* velocity can be updated. Clearly, more work is needed to generalize this method to a full wave-equation setting.

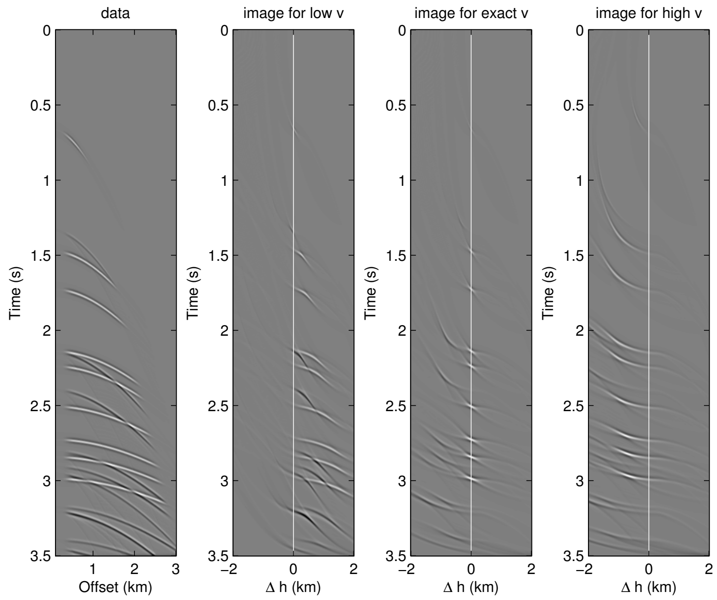

Figure 1: Migration velocity analysis on data with multiples. The first panel on the left displays the data, obtained with the convolutional model. The second image from the left shows the migration image as a function of the offset-at-depth Δh in a model with too low velocities. The third panel from the left corresponds to the correct velocity model. Now the primaries are focused at zero Δh and the multiples appear as part of upward curving hyperbolas at negative Δh. The rightmost panel shows a the migration image for too high a velocity.

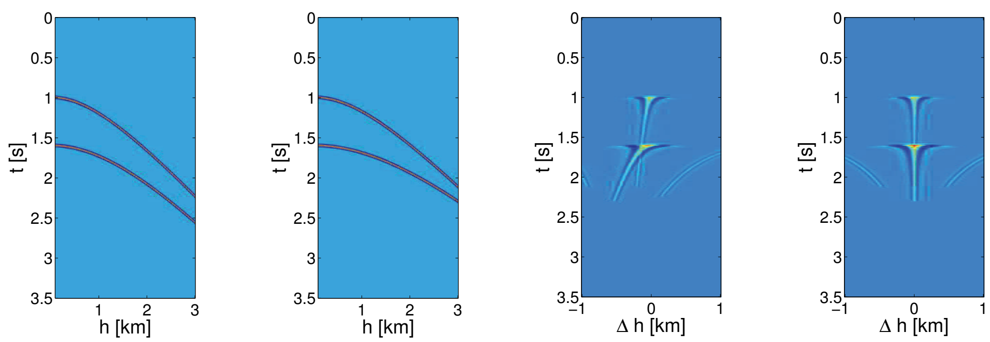

Figure 2: The two leftmost panels display data for different background velocity models. The spatial correlation of the two and the spatial auto correlation of the second panel are depicted on the right. This shows that the energy is focused around zero shift if the background velocity models of the data are equal.

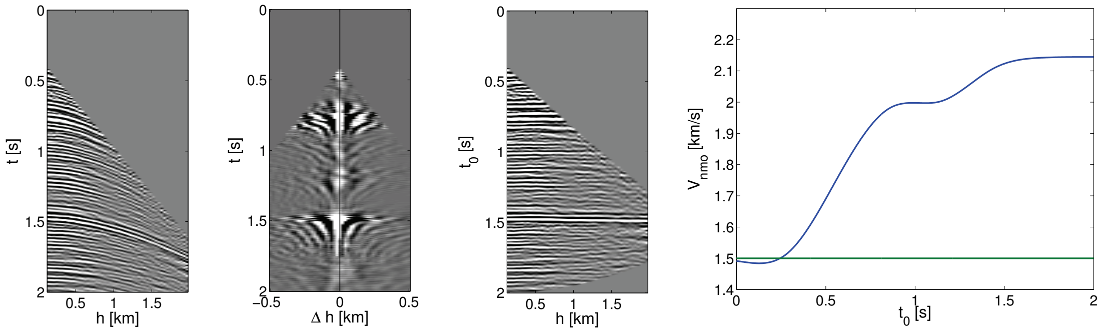

Figure 3: Example on real data from the North Sea. The velocity model was obtained by optimizing the amount of focusing of the data correlation. From left to right, the data, the data correlation, the NMO-corrected data for the final velocity model, and the initial and final velocity models are shown.

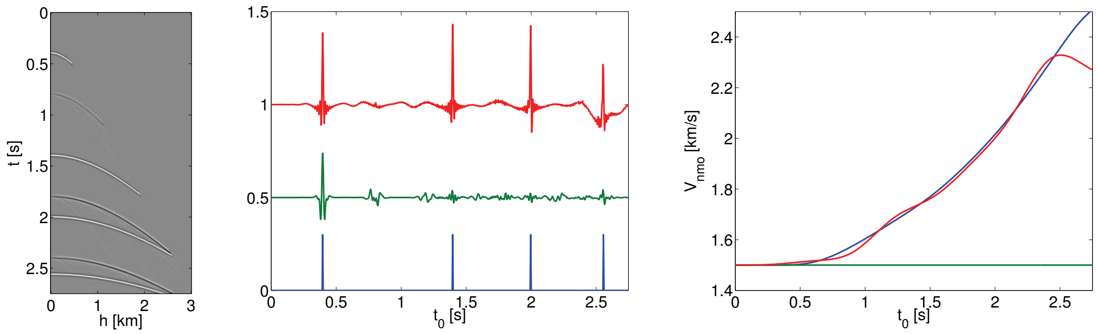

Figure 4: Example on synthetic data with multiples. The left panel shows the data. The reflectivity and velocity model were alternately updated, optimizing the LS error and the data-correlation respectively. The middle panel shows the reflectivity obtained for the initial (green) and final (red) velocity model as well as the true reflectivity (blue). The right panel shows the corresponding velocity models.

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