The effects of seismic data conditioning on prestack simultaneous impedance inversion

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It is well known among the seismic data processing community that the demands of reservoir characterization are far more rigorous than those of structural interpretation. Further, the undesired prestack seismic phenomena that need to be diminished or removed prior to reservoir characterization are also well known. The objective of this paper is to quantify the advantages of performing prestack data conditioning prior to reservoir characterization. Three specific seismic properties that will be addressed are: (1) signal-to-noise ratio (SNR), (2) offset-dependent frequency loss, and (3) gather alignment.

I have chosen a simple and straightforward method of testing the effects of data conditioning: inverting the original processed gathers as well as the conditioned gathers and measuring the difference in intermediate products at each stage in the workflow. Specifically, differences will be measured at four points: (1) the gathers input into the inversion, (2) wavelets extracted from the gathers, (3) inversion residuals, and (4) pay delineation.

Gather-conditioning methods

SNR enhancement. As pointed out in the TLE special section on seismic noise (March 2008), noise is that part of the seismic signal not utilized by the application being considered, which in this case is prestack impedance inversion. In order to reduce this undesired component of the seismic signal, we assume that any “noise” remaining after conventional processing is random. If this were not the case (for instance, if dipping coherent energy were present), dip or spatial filters would need to be used prior to SNR enhancement.

To attack the random, uncorrelatable energy component, we use a process developed by Tury Taner called “3D edge preserving smoothing.” This process works on 3D gathers by first separating the data into common-offset volumes so as not to interfere with the AVO signature of the gather. Then dip scanning is performed in a running window on all traces surrounding the target trace to determine the dip with the greatest semblance. Once local dip is determined, correlation coefficients of all surrounding traces are calculated along this local dip. Edge detection is performed by eliminating correlations below a user-specified amount, thus preserving discontinuities such as faults. The remaining trace samples are then summed in a Gaussian filter after they have been normalized and weighted with their respective correlation coefficients.

NMO stretch removal. The object is to compensate for the loss of frequency with offset caused by NMO stretch. One method of removing stretch is by the use of a cos $\theta$ operator, since stretch depends solely on the cosine of the reflection angle. Such methods seek to accurately calculate this angle, perhaps with migration operators.

Other researchers rely on a comparison between the near- and far-trace spectra to compensate for the loss of frequency with offset (Lazaratos and Finn, 2004; Xu and Chopra, 2007). Linear spectral operators are designed based on the amount of stretch at any time and offset as compared to the near offset.

This method uses the latter principle. Gabor-Morlet joint time-frequency analysis (JTFA) is used to separate the frequency spectra of each gather trace into a user-specified number of sub-bands (Singleton et al., 2006). The sub-bands are calculated using a running Gaussian-shaped window which gives a slowly varying amplitude profile of each sub-band. Then each sub-band spectrum is balanced against the corresponding sub-band of a user-specified pilot trace within the gather.

The primary advantages of this approach are: (1) the bandwidth of the gather at each time sample is determined by the pilot trace, and (2) the total energy contained in each reflector is held constant by computing its energy envelope and requiring that the energy of all sub-bands (after scaling) sum to the original energy envelope amplitude. This ensures that AVO character is not altered in this process.

Gather flattening. A basic assumption of AVO theory is that the reflectors being measured are horizontal. Unfortunately, this usually only happens with synthetic gathers. The two basic approaches to ensure recorded seismic data conform to these assumptions might be termed “velocity-based” and “statics-based.” Velocity-based methods assume non-flat reflectors are caused by residual NMO (RMO), and thus can be corrected by high-resolution estimation of the second-order rms velocity field. Statics-based methods assume local velocity perturbations in the seismic raypath cause random undulations in gather reflectors. These cannot be removed using an overall velocity field, so they are treated as static errors (Hinkley, 2004; Gulunay et al., 2007).

Our algorithm takes the “statics-based” approach. It minimizes a least-squares (L2 norm) error in a reflector by determining a time-variant statics shift on each gather trace. Shifts are calculated in a running window, typically 50–200 ms long, and are vertically smoothed to prevent jumps. The “condition” that is minimized can be one of two choices—semblance or AVO fit. Semblance is the most robust and is the one described in the articles referenced above. However, it is only applicable for AVO class I and class III anomalies. AVO class II phase rotations (especially those that are not full phase reversals) present a special problem that requires great care in addressing. For this case, we minimize the L2 norm fit error in either a two-term (Shuey) or three-term (Aki and Richards) equation. These least-squares solutions are less stable but are required where AVO class II anomalies are present or suspected.

Results

Data conditioning. The seismic data set chosen for this example is from the Norwegian Sea and has been reported on previously (Singleton, 2008). The input gathers are in fairly...
good shape, but do have characteristic ringing on the near traces deeper in the section due to water-column reverberation (Figure 1, left). The reservoir zone, at about 3.3 s, is represented by a trough. Slight wobbles in some reflectors can be seen, along with reflector loss in the far offsets between 3.0–3.2 s due to frequency loss and tuning.

Following application of the three algorithms described previously, reflectors appear continuous and flat from near to far offsets and stretch has been removed (Figure 1, right). About half of the near trace reverberation below 3.3 s has been removed.

Overall, it is readily apparent that the conditioned gather is in much better shape to perform an AVO or impedance inversion. But the question could reasonably be asked, “How much better is the conditioned gather than the raw gather?” To answer that question I used a simple measurement (there are much more sophisticated quality measures available): fit to a two-term Shuey equation (Figure 2). From this simple test, it is apparent that SNR enhancement and stretch removal had the greatest improve-
ment on the gather (14%), while alignment added another 6% to change the quality of AVO fit from 58% to 78% within the zone of interest.

AVO modeling. Since impedance inversion is basically a solution of the AVO equation, it makes sense to check reflector AVO character in the vicinity of the reservoir zone. This allows us to flag areas of gross misfit so that errors are not propagated into the inversion solution.

The first check is on the change in AVO reflectivity at the reservoir top as a result of gather conditioning. Surprisingly, even though the improvement in gather quality is readily apparent, the resulting reflector amplitude change with offset does not appreciably change (Figure 3). However, the near-offset amplitudes at the reservoir top do not seem to follow the expected AVO response of increasingly negative amplitude with offset. To check this, I compared the conditioned gather to a synthetic gather (in this case, we used a full-waveform solution that includes the effects of attenuation).

Figure 3. (top) Raw (left) and conditioned (right) gather showing the reservoir zone (red and green lines). (bottom) AVO reflectivity at the top of the reservoir interval.

Figure 4. (top) Conditioned gather (left) and full waveform synthetic gather (right) in the vicinity of the reservoir zone. (bottom) AVO reflectivity at the top of the reservoir interval. Of interest is the deviation in near-angle seismic amplitude from that of the synthetic.

Figure 5. Raw (lower) and conditioned wavelets (upper) for the four angle stacks. First panel is wavelet shape, second is amplitude spectra, and third is phase spectra. Note that the far wavelet in the raw data becomes unstable at about 30°, corresponding to a significant drop in frequency.
tion, multiples, and converted waves). This comparison demonstrates that the near-offset amplitudes are higher than they should be by a factor of about 2.5 (Figure 4). In retrospect, this amplitude behavior was expected in light of the initial observation of ringing on the near traces of the raw gather (Figure 1). Armed with this information, we can then make intelligent decisions on weights to be applied to the various angle stacks during the inversion, including a deweighting of the near-angle stack.

Wavelet extraction. The first step in the inversion workflow is to extract wavelets. Here we used the traditional method of calculating a least-squares shaping filter that, when convolved with the reflectivity series of the well, best matches the corresponding seismic trace. Wavelets were extracted for four angle stacks (10–25°, 20–35°, 27–43°, and 35–50°) for both the raw and conditioned data (Figure 5). The raw wavelets had more reverberation on their tails which is due to noise and instability in the seismic data. The raw far-angle stack lost stability at about 30°, a fact that is clear from both the frequency and phase spectra.

Figure 6. Raw far-angle stack (panel 1), inversion synthetics (panel 2), and seismic/synthetic inversion residuals (panel 3). In this case, the synthetics bear little resemblance to the angle stack and as a result the residuals look mostly like the synthetic, giving a residual-to-seismic amplitude percentage of 73%.

Figure 7. Conditioned far-angle stack (panel 1), inversion synthetics (panel 2), and seismic/synthetic inversion residuals (panel 3). The conditioned-angle stack and inversion synthetics closely match each other, giving a more favorable residual-to-seismic amplitude percentage of 30%.
Figure 8. Backus upscaled acoustic and shear impedance logs (solid line) overlain with extracted AI and SI inversion traces at the well (dashed line).

Figure 9. Inversion AI (x axis) versus SI (y axis) cross-plot for the conditioned data. Color density is number of hits. The pay capture polygons derived from the upscaled well log are shown with their hits filled in (magenta for highest porosity zone, cyan for next highest porosity zone). Black ovals within the data cloud indicate separate lithology and/or porosity clusters within the volume.

Data conditioning had the desirable effect of creating very similar wavelets in all angle-stack ranges, with the exception of a minor fall-off in high frequencies in the farther angles. Phase is similar in both sets of wavelets, which is expected because all conditioning processes we applied were phase-neutral.

Simultaneous impedance inversion. The angle stacks were inverted to AI and SI impedance using the IFP (Institut Français du Pétrole) Bayesian simultaneous inversion algorithm. This algorithm uses a model-based inversion approach where the input background model is continually modified until reaching a stable solution. It assumes that seismic noise
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Figure 10. Inversion AI (x axis) versus SI (y axis) cross-plot for the raw data. Color density is number of hits. The pay capture polygons derived from the upscaled well logs are shown with their hits filled in (magenta for highest porosity zone, cyan for next highest porosity zone). Notice that noisy data extend outside of the black ovals (compare with Figure 9). In particular, note the data contamination in the high-porosity portion of the reservoir capture.

Figure 11. Crossline through well location (vertical red dotted line on right side of panel) showing conditioned AI and SI inversion volumes (panels 1 and 2) versus raw AI and SI inversion volumes (panels 3 and 4). Pay captures shown with polygon color codes from Figures 9 and 10.

and elastic model uncertainties can be described by zero-mean Gaussian probabilities. Using those assumptions, an objective function is minimized that has both seismic and geological terms (Tonellot et al., 2001).

Inversion residuals. The first step in assessing the quality of the inversion lies with the seismic/synthetic residuals. This is because the inversion synthetic is calculated from a best-fit AVO solution of the reflectivities from all angle stacks. If any of the input angle stacks do not fit the AVO solution, this will be reflected in the difference between the inversion synthetic and the input angle stack. This is known generically as “residuals.”

The largest difference between raw and conditioned data was in the far angles because of the stretch removal applied to the seismic (Figures 1 and 3). Thus, we might expect that the raw far-angle-stack synthetics to be significantly different than the input raw far-angle stack. This in fact is the case (Figure 6). The inversion synthetic in this case is of much higher resolution and frequency than the input seismic angle stack. This fact is shown in the residuals, whose higher frequency content reflects the portion that was not originally present in the angle stack.

The opposite case exists in the conditioned data. The far-angle stack and inversion synthetic closely resemble each other, which is reflected in the low level of residual amplitude and in the similar frequency content of all three stacks (Figure 7).

We can quantify this difference by measuring rms amplitudes of these stacks: raw far-angle stack = 16.5, conditioned far-angle stack = 20.0, raw far residuals = 12.0, and conditioned far residuals = 6.0.

This results in a residual-to-angle stack amplitude ratio of 73% in the raw data and 30% in the conditioned data.

Inversion analysis. The inversion volumes were then checked. First, extracted acoustic impedance (AI) and shear impedance (SI) inversion traces were extracted at the well for both cases and matched up against Backus upscaled AI and SI well logs (Figure 8). The AI extractions were similarly accurate in both raw and conditioned data, primarily because the acoustic impedance solution is the most stable. The SI extractions showed more noise on the raw data than on the conditioned data, as we expected.

Second, the inversion volumes were crossplotted and pay signatures captured. The polygon used in the pay capture was derived from the upscaled well logs and applied to the invert-
ed data. This polygon was designed to capture only the highest quality portions of the reservoir, which I define as those portions exhibiting the highest porosity. In addition, the polygon was subdivided into two portions that would distinguish the highest relative porosity from the next highest relative porosity.

The conditioned data exhibit a much tighter cross-plot signature (Figure 9) than the raw data (Figure 10). The scatter in the raw data is entirely due to noise and uncertainty in the AVO solution. Conversely, the cluster of points in the conditioned data is so close that different lithologies can be identified due to their different $V_p/V_s$ ratios (shifts perpendicular to the mudrock trend with increasing sandiness in the NW quadrant) and different porosities (shifts parallel to the mudrock trend with increasing porosity in the SW quadrant).

The increase in cross-plot scatter in the raw data has the effect of pushing additional data points into the pay polygon, leading to increased error and uncertainty in pay capture (Figure 10). This can clearly be seen when the captured data are sent back into the seismic data volume (Figure 11). It is evident that not only has the area defined as pay grown in size, but most of it appears to be occupied by the highest porosity pay. Also evident in Figure 11 is the improvement in the character of the AI and SI inversion as a result of gather conditioning.

The final stage of this exercise is to volumetrically render the pay captures (Figures 12 and 13). Two things become immediately obvious: First, the total volume of the raw inversion pay capture (Figure 12) is substantially greater than that of the conditioned inversion pay capture (Figure 13). Thus, using the raw data to calculate geobody volumetrics would lead to erroneously high reserve estimates.

Second, the impedance range and average impedance of the geobodies in the raw inversion are lower than that of the conditioned inversion. If we volumetrically render only the high porosity polygon in Figures 9 and 10 (magenta points), the difference between the two inversions would be even more dramatic. Therefore, it is apparent that the use of unconditioned seismic data for reservoir characterization may lead to erroneously high estimates of porosity and, consequently, hydrocarbons in place.

The error in rock property calculations from both of these inversions can be quantified by calibration to well control. For instance, impedance calibration was already shown but not quantified (Figure 8). Top and base of pay capture can be compared, as can inverted rock property values (e.g., porosity) obtained from well log AI versus $\Phi$ transforms. These
calibrations will be the subject of a follow-up paper.

Conclusions
Reservoir characterization puts hefty demands on a seismic data set. Asset teams are asking for more accurate seismic estimates of hydrocarbon fluid fill and rock properties in reservoirs. To be able to meet these increasingly stringent demands, seismic data used for reservoir characterization need to be conditioned to remove as many undesirable effects as possible. Three wave-transmission effects that are commonly removed or reduced in pre-inversion gather conditioning are random noise, NMO wavelet stretch, and nonflat reflections. This paper demonstrated that data that might be considered acceptable for normal structural interpretation could still be prone to large errors when subjected to prestack impedance inversion without first being conditioned.


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