SUMMARY

We design a suite of surface-consistent matching filters for processing time-lapse seismic data in a surface-consistent manner. By matching filter we mean a convolutional filter that minimizes the sum-squared difference between two signals. Such filters are sometimes called shaping filters. The frequency-domain surface-consistent design equations are similar to those for surface-consistent deconvolution except that the data term is the spectral ratio of two surveys. We compute the spectral ratio in the time domain by first designing trace-sequential, least-squares matching filters, then Fourier transforming them. A subsequent least-squares solution then factors the trace-sequential matching filters into four surface-consistent operators: source, receiver, offset, and midpoint. We present a synthetic time-lapse example with nonrepeatable acquisition parameters and near-surface and subsurface model variability. Our matching filter algorithm significantly reduces the nonrepeatability often observed in time-lapse data sets.

INTRODUCTION

It has become an industry practice to acquire multiple seismic surveys at regular time intervals to monitor subsurface changes due to hydrocarbon production or fluid injection. As exploration seismologists, our main objective is to obtain an image that represents our best estimate of the subsurface changes. This goal is challenged by the fact that seismic acquisition is nonrepeatable, which diverts our attention from investigating only the time-lapse difference to minimizing the nonrepeatability issues of seismic acquisition. There has been significant work published on processing time-lapse seismic, in particular that of Rickett and Lumley (2001), who discuss the details of the cross-equalization process that reduces the nonrepeatable noise caused by differences in vintage of seismic acquisition and processing. Cross-equalization is based on processing two repeated seismic surveys in parallel and taking the difference between them after each step. Generally, this cross-equalization process should show a progressive decrease in nonrepeatable noise and improvement in time-lapse changes (Rickett and Lumley, 2001).

The progressive decrease in nonrepeatable noise can be an exhausting process. Instead, we propose a method that takes care of much of the nonrepeatable noise at the very beginning of the processing workflow. This method employs two basic concepts that are widely used in geophysical data processing: the surface-consistent model and matching filter. We will present an algorithm that combines both ideas and demonstrate its simplicity and advantage in processing a time-lapse data set. The synthetic data set presented here is quite complicated and resembles a real data set known to be nonrepeatable due to variations in seismic acquisition, processing and factors related to near-surface geology (Jack, 1998).

The surface-consistent model was first introduced by Taner and Koehler (1981) who suggested the recorded seismic trace can be modeled as the convolution of each trace’s source effect, receiver effect, offset effect and midpoint effect. This model is similar to the one used for solving the statics problem by Taner et al. (1974) and Wiggins et al. (1976). The surface-consistent model has been implemented by many authors to obtain a more accurate and stable deconvolution (Morley and Claerbout, 1983; Levin, 1989; Cambois and Stoffa, 1992; Cary and Lorentz, 1993), amplitude adjustment (Yu, 1985), and phase-rotation (Taner et al., 1991).

The time-domain form of the modeled seismic trace (Taner and Koehler, 1981; Morley and Claerbout, 1983) is:

\[ \hat{d}_{ij}(t) = s_i(t) * r_j(t) * h_k(t) * y_l(t) \]  

where \( \hat{d}_{ij}(t) \) is the seismic trace and "*" denotes convolution in the time domain, \( s_i(t) \) is the source effect at the \( i \)th location, \( r_j(t) \) is the receiver effect at the \( j \)th location, \( h_k \) is the offset effect, \( k = |i - j| \), and \( y_l \) is the common midpoint effect, \( l = \frac{i + j}{2} \).

Extending the surface-consistent data model to the case of designing matching filters to equalize two seismic surveys, we write equation 1 as follows:

\[ d_{1ij}(t) = s_1(t) * r_1(t) * h_1(t) * y_1(t) \]  

\[ d_{2ij}(t) = s_2(t) * r_2(t) * h_2(t) * y_2(t) \]

where indices 1 and 2 used here to denote two data sets, a baseline survey and a monitoring survey (commonly used in time-lapse studies), respectively. Computing the Fourier time transforms of equations 2 and 3, forming their ratio, and taking the logarithm of the result produces

\[ \log \left( \frac{\hat{d}_{2ij}(\omega)}{\hat{d}_{1ij}(\omega)} \right) = \log \left( \frac{\hat{s}_2(\omega)}{\hat{s}_1(\omega)} \right) + \log \left( \frac{\hat{r}_2(\omega)}{\hat{r}_1(\omega)} \right) + \log \left( \frac{\hat{h}_2(\omega)}{\hat{h}_1(\omega)} \right) + \log \left( \frac{\hat{y}_2(\omega)}{\hat{y}_1(\omega)} \right) \]  

where \( \omega \) is frequency, the hat denotes the Fourier transform, the left-hand side is the data log spectral ratio and the right-hand-side contains its surface-consistent components. This can be formulated as a general linear inverse problem (Wiggins et al., 1976) such that

\[ Gm = d. \]

where \( G \) represents the seismic geometry matrix (similar to that shown in Figure 1), \( m \) is a vector of surface-consistent terms, and \( d \) is a vector of log-spectral ratios. The number of columns of \( G = total\ number\ of\ sources + total\ number\ of\ unique\ receivers + total\ number\ of\ unique\ offsets + total\ number\ of\ midpoints \) and the rows of \( G = total\ number\ of\
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Figure 1: Matrix structure of the system of linear equation described in equation 5; the number of columns of \( G \) = number of sources + number of unique receivers + number of unique offsets + number of midpoints and the number of rows of \( G \) = total number of traces; the length of \( d \) = total number of traces.

traces, and that is equal to the length of \( d \). The computation of the data spectral ratio by direct division in the frequency domain, shown in equation 4, is unstable due to the presence of noise in the seismic data. As a stable alternative, we compute a trace-sequential matching filter in the time-domain for each pair of traces in the two surveys. The design equations for this filter are:

\[
\sum_t (m(t) * d_2(t) - d_1(t))^2 = \min
\]

where \( d_1 \) and \( d_2 \) represent the same trace from surveys 1 and 2, respectively, and \( m(t) \) is the trace-sequential matching filter. Once this trace-by-trace matching filter is computed for all trace pairs, the result is transformed into the frequency-domain (Figure 2), giving a stable estimate of the left-hand side of equation 4.

EXAMPLE AND DISCUSSION

To examine our new idea, we constructed a simple 2.5 km wide and 1 km thick 2D model. The model consists of four layers and a reservoir unit, 500 m wide and 20 m thick, between layers three and four. The velocity is homogeneous in each layer, except for the near-surface layer where lateral variations were introduced. Using this geometry, we generated two earth models, a baseline model and a monitoring model (Figure 3a and b), with different near-surface and reservoir velocities (Figure 3c and d). The number of shots used was 51 at 50 m with a receiver array of 101 geophones at a 10 m interval. The maximum record length is 1 s with a 4 ms sampling interval. An acoustic finite-difference modeling algorithm was used to acquire the data. We have also added random variations to shot strengths, receiver couplings, and near-surface attenuation to allow for the nonrepeatability observed in real seismic acquisition. In Figure 4a and b we show an example of a single shot record located at x-coordinate 1250 m from both the baseline survey and the monitoring survey, respectively. The computed four-component surface-consistent matching filters are applied to the monitoring survey and the result is shown in Figure 4c. The difference between the baseline survey shot record and the matched monitoring survey shot record is illustrated in Figure 4d, and all plots have the same amplitude scaling as the baseline shot record. The difference is very small inside the matching filter window between the two red lines (approximately 300 ms above the reservoir unit). In addition to this qualitative analysis of the difference, we computed the NRMS (normalized root mean square), in the window of analysis, where small
NRMS values indicate similarities between the traces of the baseline survey and the matched monitoring survey. NRMS is computed using the following relationship discussed in Kragh and Christie (2002):

\[
NRMS = \frac{\text{rms}(\text{base} - \text{monitor})}{\text{rms}(\text{base}) + \text{rms}(\text{monitor})}.
\] (7)

Preferred values for NRMS are in the 20 to 30% range and those values are commonly obtained towards the final stages of processing, i.e. post migration and final stacking. Our new technique was able to reduce the difference quite significantly down to about 25% in the prestack stage after only applying the surface-consistent matching filters. In Figure 5a and b we show the stacks of the baseline survey and the matched monitoring survey, respectively, after correcting for the residual statics in a surface-consistent manner. We applied two passes of matching filters to the shots of the monitoring survey in order to minimize the difference discussed in equation 6. The difference between the baseline survey stack and the matched monitoring survey stack is shown in Figure 5c. It is critical to note that only three steps of processing have been applied at this stage: 1) applying the matching filters to the monitoring survey, 2) NMO removal and residual statics correction, and finally 3) stacking. The NRMS values prior to step 1 were averaging 80% whereas after applying step 1, NRMS values significantly decreased to around 25%. NMO removal, residual statics correction and stacking marginally improved our result, and the NRMS values averaged around 16%.

CONCLUSIONS

We have developed a method to design surface-consistent matching filters that can be used to match one data set to another in a time-lapse experiment. Our method is similar to surface-consistent deconvolution except that the data required are the spectral ratios of each pair of traces in the survey. We compute the spectral ratios in a stable fashion as the Fourier transform of a least-squares matching filters for each pair of traces. Then we factor these trace sequential matching filters into surface-consistent terms by a second least-squares solution. We have shown that the surface-consistent matching filters can significantly reduce the nonrepeatability often observed in time-lapse data sets.

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Figure 4: An example of a shot record acquired at the same position from the baseline survey (a) and the monitoring survey (b). The red lines show the design window for the trace-sequential match filters. In (c) is the result of applying the four-components matching filters to the shot in (b). The difference between (a) and (c) is illustrated in (d). The two red lines represent the matching filters length.

Figure 5: Baseline survey CMP gathers stack (a) after three passes of surface-consistent residual statics. (b) shows the monitoring survey CMP gathers stack after applying matching filters and correcting the residual statics. In (c) is the difference between (a) and (b) and the NRMS plot is shown in (d).