# Optimized local matching of time-lapse seismic data: A case study from the Gulf of Mexico

*Gboyega Ayeni*, Stanford University and Mosab Nasser, Shell International E & P*



## SUMMARY

We discuss a method for selecting optimal filter lengths, trace segments and damping parameters for local-matching of time-lapse seismic data sets. In this method, an evolutionary programming (EP) algorithm is used to optimize parameters such that estimated match filters have predefined properties within and outside the estimation window. Results from a 3D time-lapse data set from the Gulf of Mexico show that this method provides improvements over conventional local-matching that use fixed, manually selected filter estimation parameters.

## INTRODUCTION

Time-lapse (4D) seismic is a proven technology for monitoring hydrocarbon reservoirs and is now central to most field development and management plans (Landrrø et al., 2001; Marsh et al., 2003; Whitcombe et al., 2004). A recurring challenge in time-lapse seismic applications is non-repeatability resulting from difficulties in replicating the same acquisition geometry for different surveys. Therefore, time-lapse seismic images usually require additional processing (cross-equalization) before they can be interpreted for reservoir changes.

The estimated seismic amplitude changes at the reservoir depend on the equalization methods applied to the seismic data sets. A wide variety of equalization methods can be implemented at different stages of processing, but here we are concerned with post-stack match filter-based methods. A procedure for such methods can be broadly summarized as follows:

- Event-alignment: Correction for time-shifts caused by geomechanical effects and velocity changes using warping or local cross-correlation methods.
- Matching: Global and/or local match filtering of the base and monitor images within a window outside the reservoir region to remove unwanted phase and amplitude differences between the images. In some implementations, this step is usually preceded by spectral shaping and amplitude balancing.

We aim to improve the filter estimation process and also reduce some of the undesirable match filter attributes. Conventionally, a single window (outside the reservoir) is used to estimate match filters, which are then applied to the full data set. This is limiting, because there is no guarantee on the performance of the filters when applied to an area outside the estimation window – where, for example, there are no changes in reservoir properties. There is also no guarantee that the filters will attenuate artifacts and not contaminate the true time-lapse seismic signal in the reservoir region (Lumley et al., 2003). Furthermore, parameters for estimating the match filters are typically manually selected and are usually assumed to be stationary throughout the seismic volume. However, while the chosen parameters may be suitable in certain parts of the seismic volume, they may perform very poorly in other areas. For example, the optimal length of a local match filter is non-stationary from trace-to-trace.

We improve the filter estimation process by optimizing the parameter selection process with an evolutionary programming (EP) algorithm. We use multiple time-windows above and below the reservoir region, with one set of windows used for filter estimation and the other for validation.

In this paper, we first summarize the least-squares formulation of the match filter estimation problem. We then outline an estimation strategy that utilizes an EP algorithm for parameter selection. Finally, using a 3D data set from the Gulf of Mexico, we show that the proposed method improves cross-equalization, and hence gives more accurate time-lapse amplitudes within the reservoir interval.

## MATCH FILTER ESTIMATION

Given two seismic traces ($b$ and $m$), a filter $f$ that matches the two is one that minimizes the residual $r$ in the equation

$$r = f * m - b, \tag{1}$$

where $*$ represents convolution. In the time-lapse problem, traces $b$ and $m$ are traces extracted from a window inside the baseline and monitor data sets. Equation 1 can be re-written in two equivalent matrix-vector forms as follows:

$$r = Fm - b, \tag{2}$$

or

$$r = Mf - b, \tag{3}$$

where $F$ and $M$ are convolution matrices built from the filter coefficients and monitor data respectively. Equation 3 can be minimized using any norm, but we follow a least squares approach, for which we can write

$$f = (M'M)^{-1}M'b. \tag{4}$$

We can solve this in the frequency domain as follows:

$$\mathbf{F}(w) = \frac{\overline{\mathbf{M}}(w)\mathbf{B}(w)}{\overline{\mathbf{M}}(w)\mathbf{M}(w)}, \tag{5}$$

where $\overline{\mathbf{M}}(w)$ is the complex conjugate of the monitor data. In order to avoid zero division, a damping factor $\varepsilon$ is included in the denominator of equation 5 so that we have

$$\mathbf{F}(w) = \frac{\overline{\mathbf{M}}(w)\mathbf{B}(w)}{\overline{\mathbf{M}}(w)\mathbf{M}(w) + \varepsilon^2}. \tag{6}$$

Zero-division can also be avoided by reducing the roughness of the frequency spectra with a smoothing function, $<>$:

$$\mathbf{F}(w) = \frac{<\overline{\mathbf{M}}(w)\mathbf{B}(w)>}{<\overline{\mathbf{M}}(w)\mathbf{M}(w)>}. \tag{7}$$

Equation 6 or 7 can be used to compute a single global matching filter for the whole data set or local-matching filters at each trace location. In many implementations (e.g. Rickett and Lumley (2001)), global match filtering is followed by local-matching of the data sets. We limit our discussions in this paper to local filters which we compute using equation 6.

## PARAMETER OPTIMIZATION

The local match filters derived from equation 6 are a non-linear function of the filter parameters. Usually, practitioners select estimation parameters through a manual *trial-and-error* approach. This can be a tedious or impossible challenge due to the strong non-linearity of the problem and the large size of seismic data sets. In this section, we summarize a simple optimization method that can be used to select the best parameters for filter-estimation.

### Evolutionary programming (EP)

EP belongs to a class of global optimization methods called evolutionary algorithms. These algorithms solve optimization problems using Darwinian evolutionary principles of natural selection. A basic evolutionary algorithm pseudocode is summarized as follows:

```
Initialize the population
Evaluate initial population
Loop
    Generate new solutions from current
        ones using genetic operators
    Evaluate all solutions in the population
    Perform competitive selection of
        solutions within population
until convergence criteria is satisfied
```

Application of evolutionary algorithms (EA) to seismic problems is not new. Published examples include waveform-inversion (Sambridge and Drijkoningen, 1992), horizon-tracking (Aurnhammer and Tonnie, 2005) and wavelet estimation (Yang et al., 2007). Genetic algorithms (GA) are the most common members of the EA family, but we use EP because of its simplicity and ease of implementation. The most important implementation considerations include the population size and initialization, the mutation operator, and the selection/rejection criterion. Selecting an appropriate error/fitness function is also important, because this determines which of the solutions are kept and which are rejected.

### Workflow

The simplified workflow in Figure 1 summarizes the application of EP to parameter selection in the filter estimation problem. Estimation and validation windows are defined outside the reservoir. The EP algorithm optimizes the estimation window (by defining new trace-segments and the ramp-off within the estimation window at each trace location), the filter length and the damping factor in equation 6. We define the error function as the weighted repeatability, *rrr*, computed within the validation windows as follows:

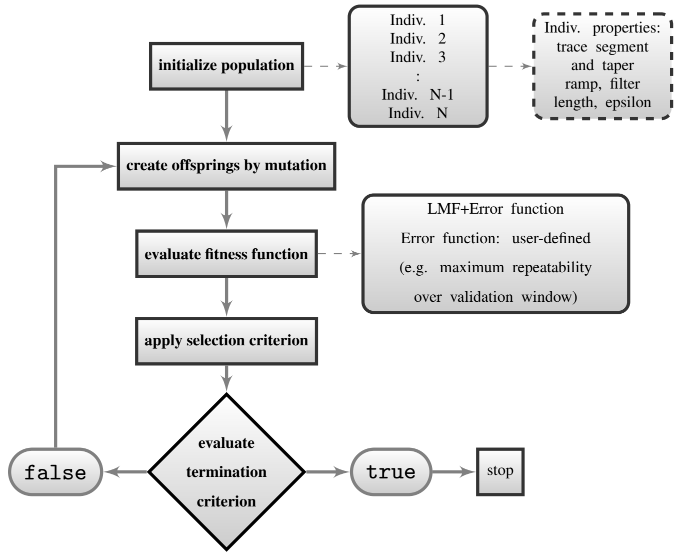



Figure 1: Evolutionary programming workflow for selecting estimation parameters for local match filters.

$$rrr = 2 \times \frac{(b-m)_{rms}}{b_{rms} + m_{rms}}, \tag{8}$$

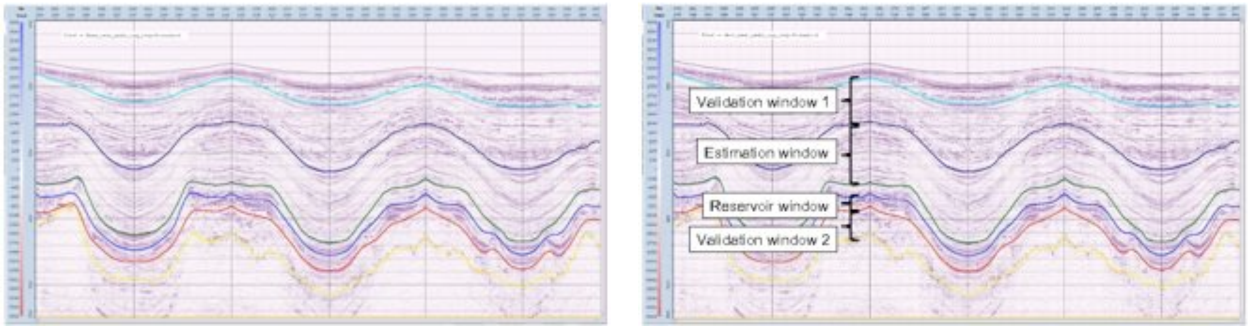
where $b_{rms}$ and $m_{rms}$ are the root-mean-square energy from the baseline and matched-monitor trace segments, respectively.

## EXAMPLE

We applied this method to a time-lapse data set from the Holstein field located in the Gulf of Mexico. The baseline is a single-vessel data set acquired in 2001, whereas the monitor is a dual-vessel data set acquired in 2006. The data sets were processed using a 4D parallel processing workflow that includes 4D-binning and regularization, differential statics, multiple attenuation, acquisition footprint removal and pre-stack depth migration. A detailed review of acquisition and processing of the Holstein time-lapse data sets is given by Ebaid et al. (2008).

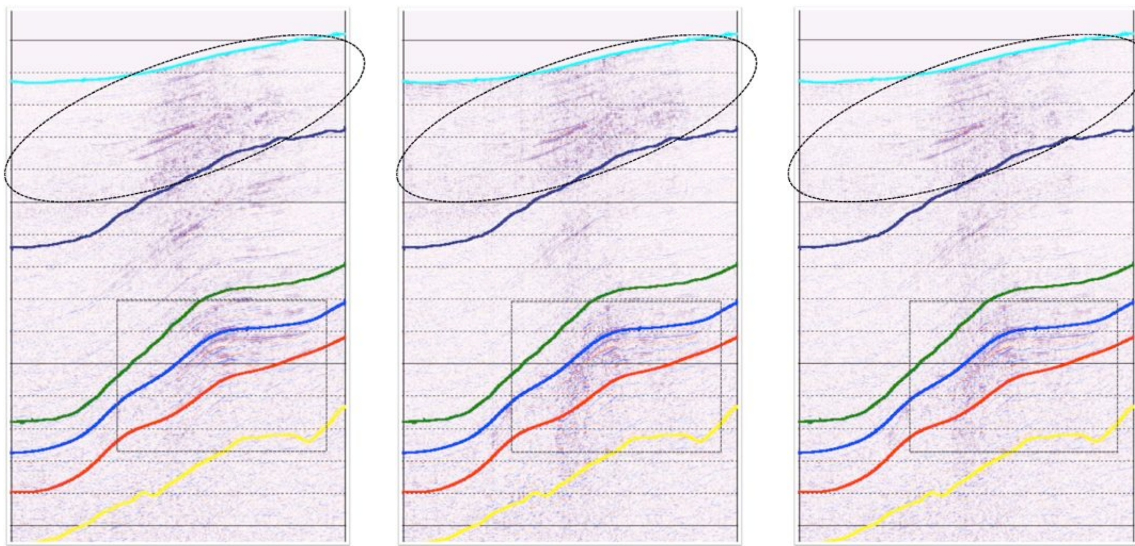
First, we aligned the data sets by applying time-shifts (not shown) that were computed with a local cross-correlation technique. Figure 2 shows the baseline and time-shifted monitor along an arbitrary traverse, $TRX$, and the positions of the estimation and validation windows. After several tests, we selected the best estimation parameters and compared the results from the derived filter with those obtained from optimized parameters. We used a fixed 3x3 mixing window around each trace for both the time-shift and filter estimation.

Time-lapse difference sections through a segment of traverse $TRX$, before and after match filtering, are shown in Figure 3. Note the high-amplitude undershoot artifacts above the reservoir, where production facilities obstructed the monitor survey.




(a) (b)

Figure 2: (a) Base and (b) monitor data sets through traverse $TRX$ shown in Figure 4. The estimation window and two validation windows above and below the reservoir window are shown in (b).



(a) (b) (c)

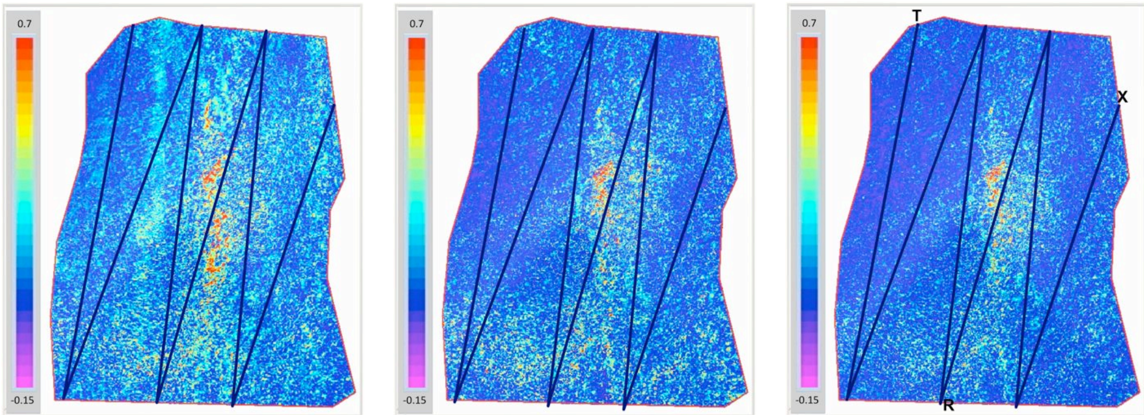
Figure 3: Time-lapse difference images obtained (a) before and after filtering with match filters from (b) the best fixed set of parameters, and (c) optimized filter parameters. Note that optimally-filtered images contain fewer artifacts outside the estimation window (ovals) and that the time-lapse image around the reservoir (rectangular boxes) is improved.

Figure 4 shows repeatability values along a horizon at the top of the estimation window before and after filtering. This window contains only artifacts since no production-related changes exist. The high-amplitude artifacts at the centre of the polygons in Figure 4 occur at the undershoot position.

Time-lapse seismic amplitudes, extracted at the top of a producing and target reservoir are shown in Figure 5. One of the goals of this time-lapse survey is to ascertain whether hydrocarbon has been drained from a drilling target adjacent to the producing reservoir (see Figure 5). Note that the unmatched time-lapse data set show no amplitude changes around the target area, whereas the filtered data sets show amplitude changes.

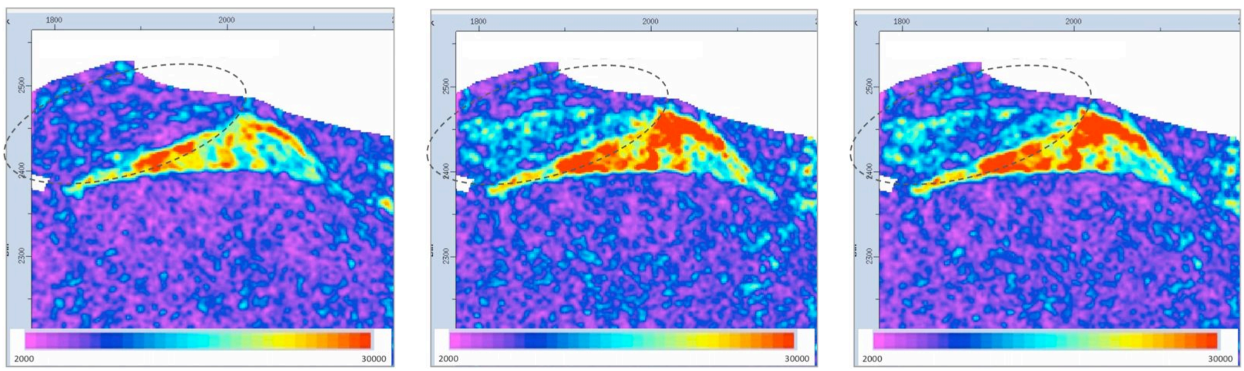
## DISCUSSION AND CONCLUSIONS

Artifacts in the time-lapse image are better attenuated with the optimized filters (Figure 3). Although the filters obtained from fixed parameters attenuate the artifacts within the estimation window, they also increase the artifacts outside this window (Figure 3(b)). In particular, note the increased noise amplitudes in the top validation window. Such filtering artifacts are propagated to the reservoir window, and if uncorrected, they contaminate production-related amplitude changes. These filtering artifacts are attenuated by the optimized filters because they account for artifacts outside the estimation window (Figure 3(c)).




(a) (b) (c)

Figure 4: Horizon maps through the repeatability volume at the top of the estimation window (see Figure 2) showing repeatability measures before matching (a), and after matching using fixed (b) and optimized (c) filter parameters. The black zig-zag line indicates the arbitrary traverse $TRX$ shown in Figure 2




(a) (b) (c)

Figure 5: Extracted time-lapse amplitude maps above a target reservoir region before matching (a), and after matching using fixed (b) and optimized (c) filter parameters. Note the strong amplitude difference within the ovals in the filtered results. The optimally-filtered results contain fewer artifacts.

Optimized filters improve repeatability within the estimation window relative to the fixed-paramter filters (Figure 4). Our study of the repeatability volumes shows that there is even better improvement outside the estimation window. In general, such improved repeatability outside the estimation window translates to cleaner time-lapse images within the reservoir window. This is important since the matching goal is to attenuate non-production-related energy. A study of time-lapse amplitudes shows that optimized filters reduce filtering-artifacts both within and outside the reservoir window.

Carefully designed local match filters can significantly improve time-lapse seismic amplitudes (Figure 5). Filtering with carefully chosen filter parameters clearly highlights the amplitude changes (previously unseen in the unmatched data) in the target area. Although fixed-parameter filters highlight these time-lapse changes, they also introduce artifacts outside the reservoir region (Figure 5(b)). This may suggest that the amplitudes seen in the target sands may be spurious signals. However, results from the optimized filters (Figure 5(c)) show a more enhanced amplitude changes around the target area, with less artifacts outside the region. New drilling (not shown) results are being studied to confirm these results.

One drawback of the proposed technique is that it is computationally intensive, requiring a solution to equation 6 for each member of the population. However, since the filters are computed locally, the problem is embarrassingly parallel, allowing very fast computations. We also note that although this method achieves improved matching, there are still significant residual artifacts from the undershoot. Ayeni and Biondi (2008) discuss an inversion scheme that attenuates such artifacts.

## ACKNOWLEDGMENTS

The authors would like to thank Shell and BP management for permission to publish this work. The authors would also like in particular to thank Mike Stovall and Paul Hatchell for their suggestions and support making the timely conclusion of this work possible.

**EDITED REFERENCES**

Note: This reference list is a copy-edited version of the reference list submitted by the author. Reference lists for the 2009 SEG Technical Program Expanded Abstracts have been copy edited so that references provided with the online metadata for each paper will achieve a high degree of linking to cited sources that appear on the Web.

**REFERENCES**

Aurnhammer, M., and K. Tonnie, 2005, A genetic algorithm for automated horizon correlation across faults in seismic images: IEEE Transactions on Evolutionary Computation, **9**, 201–210.

Ayeni, G., and B. Biondi, 2008, Joint wave-equation inversion of time-lapse seismic data: Stanford Exploration Project Report, **136**, 71–96.

Ebaid, H., A. Tura, M. Nasser, P. Hatchell, F. Smit, N. Payne, D. Herron, D. Stanley, J. Kaldy, and C. Barousse, 2008, First dual-vessel high-repeat gom 4D survey shows development options at Holstein Field: The Leading Edge, **27**, 1622–1625.

Landrø, M., L. K. Stronen, P. Digranes, O. A. Solheim, and E. Hilde, 2001, Time-lapse seismic as a complementary tool for in-fill drilling: Journal of Petroleum Science and Engineering, **31**, 81–92.

Lumley, D., D. C. Adams, M. Meadows, S. Cole, and R. Wright, 2003, 4D seismic data processing issues and examples: 73rd Annual International Meeting, SEG, Expanded Abstracts, 1394–1397.

Marsh, J., D. Whitcombe, S. Raikes, R. Parr, and T. Nash, 2003, BP's increasing systematic use of time-lapse seismic technology: Petroleum Geoscience, **9**, 7–13.

Rickett, J. E., and D. E. Lumley, 2001, Cross-equalization data processing for time-lapse seismic reservoir monitoring: A case study from the Gulf of Mexico: Geophysics, **66**, 1015–1025.

Sambridge, M., and G. Drijkoningen, 1992, Genetic algorithms in seismic waveform inversion: Geophysical Journal International, **109**, 323–342.

Whitcombe, D. N., J. M. Marsh, P. J. Clifford, M. Dyce, C. J. S. McKenzie, S. Campbell, A. J. Hill, R. S. Parr, C. Pearse, T. A. Ricketts, C. P. Slater, and O. L. Barkved, 2004, The systematic application of 4D in BP's North-West Europe operations — 5 years on: 74th Annual International Meeting, SEG, Expanded Abstracts, 2251–2254.

Yang, P., X. Yin, and G. Zhang, 2007, Research on poststack seismic blind inversion: 77th Annual International Meeting, SEG, Expanded Abstracts, 1967–1971.