Seismic Pattern Recognition via Predictive Signal/Noise Separation

ABSTRACT

Manual stratigraphic interpretation of modern 3-D seismic images is extremely time-consuming. We present a method based on nonstationary predictive signal/noise separation for automatically recognizing the occurrence of a predefined pattern in seismic images. The method is tested on 2-D synthetic and real seismic images, and is shown to reliably detect the presence of unconformities in both.

INTRODUCTION

A properly stacked or migrated seismic image can be conceptualized as a single-valued spatial function of local dip angle (cite Harlan? Local slant stack). Loosely, the process of seismic facies analysis is the analysis of the dip distribution (or dip spectrum) of a seismic image in small neighborhoods and the corresponding association with a given stratigraphic sequence. The interpreter’s job, illustrated in Figure 1, is both tedious and time-consuming if performed manually, considering the large size of modern 3-D surveys. For instance, if a given sedimentary unit is best defined by its relative distance from a pervasive geologic unconformity, the interpreter must first identify the location of the unconformity over the entire seismic volume.

Figure 1: Seismic facies analysis: Given a facies template (left), search a seismic image locally (center) for likely matches to the template, then output (right) an attribute which illustrates some measure of local similarity between the template and the seismic image.

To make the stratigraphic interpretation of large 3-D image volumes feasible, an automatic approach is required to search an image locally for the likely presence of a predefined ordered pattern, or facies template. Randen et al. (1998) presented an automated scheme
which analyzes local dip spectra to detect reflector terminations in seismic images, and hint that such an approach could be used to detect unconformities and recognize facies patterns.

We present a scheme to automatically search a seismic image for an arbitrary, ordered facies template, and then to output a similarity attribute which expresses the data’s relative local resemblance to the template. To compute the similarity attribute, we recast this problem of pattern recognition to one of signal/noise separation, i.e., treating the facies template as the “noise model”, remove an optimal amount of it from small data windows and define the attribute as the local noise-to-signal ratio. It follows that the similarity attribute is both physically meaningful and optimal in one (least squares) sense - two qualities which many seismic attributes lack.

We first test the scheme on a 2-D synthetic seismic image with two unconformities, and find that both are detected reliably. We then perform the same test on a 2-D real seismic image, and successfully detect an unconformity.

![Diagram](image)

Figure 2: For each output point, extract a neighboring window of data the same size as the facies template. Capture the local dip spectra of the facies template and data window with simple nonstationary “steering filters”. Treating the facies template as the “noise” model, apply a predictive signal/noise separation technique to extract energy from the data window where the local dip coincides with that of the template. The output, simply the noise-to-signal ratio, is then a valid measure of local similarity.

**METHODOLOGY**

Consider local windows of the seismic image to be the simple superposition of signal and noise:

$$d = s + n.$$  \hspace{1cm} (1)
The frequency domain representation of the Wiener optimal reconstruction filter for uncorrelated signal and noise is (Castleman, 1996; Leon-Garcia, 1994):

\[
H = \frac{P_s}{P_s + P_n}
\]  

(2)

where \( P_s \) and \( P_n \) are the power spectra of the unknown signal and noise, respectively. Multiplication of \( H \) with the data spectrum gives an optimal (in the least squares sense) estimate of the spectrum of the unknown signal.

Abma (1995) solved a constrained least squares problem to separate signal from spatially uncorrelated noise:

\[
\begin{align*}
N_n &\approx 0 \\
\epsilon S s &\approx 0 \\
\text{subject to} & \iff d = s + n
\end{align*}
\]

(3)

where the operators \( N \) and \( S \) represent \( t - x \) domain convolution with prediction-error filters (PEF’s) which decorrelate the unknown noise \( n \) and signal \( s \), respectively, and the factor \( \epsilon \) balances the energies of the residuals. Explicitly minimizing the quadratic objective function suggested by equation (3) leads to the following expression for the predicted signal:

\[
s = N^T N \left( N^T N + \epsilon^2 S^T S \right)^{-1} d
\]

(4)

Since the frequency response of the PEF approximates the inverse spectrum of the data used to estimate it, we see that Abma’s approach is equivalent to Wiener reconstruction.

If the noise is assumed a priori to be spatially uncorrelated, as in Abma (1995), the noise decorrelator \( N \) is simply the identity, while the signal decorrelator \( S \) can be estimated reliably from the data, i.e., \( S = D \), where \( D \) is a data decorrelating filter. Otherwise, if the noise is correlated spatially, an explicit noise model is required to estimate \( N \), and an approach like the one used by Spitz (1999) to estimate \( S \). Modifying equation (3) to reflect Spitz’s choice of \( S = D N^{-1} \) and applying the constraint \( d = s + n \) gives

\[
N s \approx N d \\
\epsilon D N^{-1} s \approx 0.
\]

(5)

When solved iteratively, the problem can be preconditioned to improve convergence. Following Fomel et al. (1997), make the change of variables

\[
s = (D N^{-1})^{-1} p = N D^{-1} p
\]

(6)

and rewrite equation (5):

\[
N N D^{-1} p \approx N d \\
\epsilon p \approx 0.
\]

(7)

?) solved equation (7) iteratively to suppress ground roll with complicated moveout patterns, where \( S \) and \( N \) are nonstationary \( t - x \)-domain PEF’s.
Unfortunately, the estimation of nonstationary PEF’s is computationally costly, and it is often difficult to ensure that the filters obey the minimum-phase requirement, necessary for stable deconvolution, as in equation (7). For the application at hand, the final result is not the estimated signal and noise, but simply the noise-to-signal ratio. It follows that the separation need not be perfect - just good enough to distinguish between regions of the data with gross similarity to the facies template from the rest of the data. Also, since the interpretation is performed on stacked or migrated seismic images, the local dip should be an unambiguous single-valued function of space (no "crossing dips"). Not surprisingly, we have found that simple three-point “steering filters” (Clapp et al., 1997), work well for the noise and data decorrelating filters, \( N \) and \( D \), required to solve equation (7). The only thing needed to set up the steering filters is an estimate of the local dip field of the data and facies template, for which the automatic dip scanning technique of Claerbout (1992) produces satisfactory results.

**RESULTS**

**Synthetic Data Test**

Figure 3 shows the synthetic seismic dataset and associated local dip estimate. Figure 4 shows the facies templates used to test the algorithm and their corresponding local dip estimates. The seismic data is a 200x100 2-D slice of the “quarter dome” 3-D model used to test seismic coherency algorithms (Claerbout, 1998; Schwab, 1998), and is characterized by two unconformities. The facies templates, 30x30 points each, are designed to resemble the upper and lower unconformities, respectively, but are not windowed directly from the data itself.

Figures 5 and 6 show the output of the pattern recognition program, where the experiments were designed to detect the upper and lower unconformities, respectively. The results are good, but expected, given the high quality of the estimated dip, and provide adequate proof of concept.

**Real Data Test**

Figure 7 shows the real 2-D seismic image and its associated local dip estimate. The image processed here is a 200x200 subwindow from a migrated 2-D section originally acquired by Mobil in (year?) over a Gulf of Mexico prospect. The upper portion of the windowed data is characterized by an unconformity. Figure 8 shows the facies template used to test the algorithm and the corresponding local dip estimate. The 50x50 template was created artificially and is designed to resemble the unconformity in the data.

The quality of the dip estimates is critical to the success of the algorithm, but unfortunately these estimates are more prone to error with real data than they are for synthetic data (Compare Figures 3 and 7). In order to maximize the spatial coherency of the input data, and hence the robustness of the dip estimate, some smoothing of the data may be
Figure 3: Left: Synthetic data, a modification of the “quarter-dome” model. Right: Estimated local dip.

Figure 4: Top: Facies templates, corresponding to the upper and lower unconformities in the data (Figure ??), respectively. Bottom: Estimated local dip of facies templates shown above.
Figure 5: Left: Synthetic data. Center: Output similarity attribute, relative to upper unconformity. Right: Local data windows corresponding to the 97th percentile and higher values in the similarity attribute.  

Figure 6: Left: Synthetic data. Center: Output similarity attribute, relative to lower unconformity. Right: Local data windows corresponding to the 97th percentile and higher values in the similarity attribute. 

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Figure 7: Left: Sub-window from real 2-D seismic image. Right: Estimated local dip.

Figure 8: Left: Facies templates, corresponding to the unconformities in the upper part of the data (Figure 7). Right: Estimated local dip.
required prior to processing. In this case, the estimated dip field was smoothed using a local weighted mean filter, where the weights are the so-called “normalized correlation” measure of Claerbout (1992) - roughly speaking, a measure of the data’s local “plane-waveness”.

Figure 9 shows the output of the pattern recognition program. The results are excellent, having effectively done the same job as a human interpreter, even with a less-than-perfect dip estimate (Figure 8).

**CONCLUSIONS**

Direct subtraction: poor discriminant - want more binary approach; either this data is signal or it’s noise.

Convolution/output residual: non-intuitive result, optimality?

Interesting that steering filters can do the job. Applications: coherency, etc.

Everything depends on the dip estimate.

Performance. The program required approximately 5 minutes of computer time on one processor of SEP’s SGI Origin 200. We process only every fifth output point, for a total of 800, implying a rate of around 160 output points per minute - a figure which depends on the size of the facies template.
REFERENCES


