

## Summary

Stacking velocity analysis is one of the most important routine in seismic data processing, and it is commonly performed by sweeping a series of user-defined velocity candidates over the CMP gathers. So far, semblance is the standard solution to estimate candidate velocity. The main advantage of using semblance is its robust and disadvantage is the poor resolution. Unfortunately, in many interesting situations, we need higher resolution spectra to get an accurate velocity function, such as residual velocity analysis.

Signal-noise (SN) ratio, which is based principal component analysis (PCA), is one of the high-resolution techniques. The main shortage of PCA analysis is that strong reflection events have huge SN values compared to that of relative weak reflection events. This disadvantage make us hard to pick velocity in one SN display. In this paper, we combine the desirable characteristics of semblance and principal component analysis to generate high resolution velocity spectra.

## Methodology

#### Semblance

The semblance coefficient  $S_c$  was defined by Niedel and Taner(1971)

$$S_{c} = \frac{\sum_{i=1}^{N} \left(\sum_{j=1}^{M} d_{i,j}\right)^{2}}{N \sum_{i=1}^{N} \sum_{j=1}^{M} d_{i,j}^{2}}$$
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where *j* is the trace index and *i* is the sample index in each trace. To form the sums, N samples are taken from M traces in a window centered about  $t_0$  axis (Figure 1a). This measurement has been described as a ratio of input to output energy.

#### Eigen structure velocity analysis

Grouping samples from M geophones groups into a 1 x M vector gives

$$d(t) = s(t) + n(t) \tag{2}$$

where d(t) is the seismic traces, s(t) is the reflection signal, and n(t) is the noise

$$d(t) = (d_1, ..., d_M)$$
  $s(t) = (s, ..., s)$   $n(t) = (n_1, ..., n_M)$ 

taking the outer product of d(t) and  $d^{T}(t)$  (here T donate transpose), then we get

$$d^{T}d = s^{T}s + s^{T}n + n^{T}s + n^{T}n \qquad (3)$$

Taking the expectation of equation (3) gives

$$R = E(s^T s) + \sigma_N^2 I \tag{4}$$

(1) As  $E[s^T s]$  is a rank 1 matrix it has only one nonzero eigenvalue given by , the variance of the received signal.

(2) The minimal eigenvalue of R is , the variance of the noise

(3) The major eigenvalue of R is

Equation (4) suggest giving an estimated signal-to-noise ratio (S/N)

$$S / N = \frac{\lambda_1 - \sum_{i=2}^{M} \lambda_i}{\sum_{i=2}^{M} \lambda_i}$$

# High Resolution velocity analysis using principal components

# Bo Zhang, J. Tim Kwiatkowski, and Kurt J. Marfurt



Figure 1: Data vectorizing model. (a) Initial da t a windowing along a hyperbolic trajectory specified by zero-offset time and velocity. N samples centered about a hyperbolic trajectory are extracted from each M data trace. (b) Windowed samples form an N by M matrix. N rows become vector time samples used in determination of the covariance matrix. (c) Groups of samples within each vector [as shown in (b)] are summed to produce N reduced vectors containing M' samples each. (Scott 1990)

## ConocoPhillips School of Geology & Geophysics, University of Oklahoma





"blocks". (b) The zero-offset time is divided into adjacent data blocks of variable time duration, indicated by the dashed line. (c) rectangle window is derived based on the data blocks shown in (b), the scaling value come form the peak semblance values in each semblance block. SN before (d) scaled and after (e) scaled by the window function shown in (c).



#### Conclusions

• Principal-based signal-noise-ratio has higher resolution compared to that of conventional semblance.

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### Application