Summary

We present an overview of new and recent applications of multivariate geostatistical filtering techniques applied to 3D and 4D processing.

Introduction

When redundancy of seismic data exists factorial cokriging enables the estimation of (1) a common part, based on the common spatial behavior, and (2) the differences relative to the common part of the input data. Coléou (2002) first introduced the automatic implementation of factorial co-kriging (AFACK) as a filtering technique for the time-lapse (4D) processing sequence. It was specifically designed to optimize the critical time-lapse information such as the repeatability and the 4D seismic signature. However, over the last two years we have been developing new applications of this technique in very different processing environments. For example, applications providing data reduction, such as stacking or AVO and EI analysis, have a direct interest in the common part of consecutive offset cubes. Furthermore, we have successfully applied AFACK to more specialized problems such as the merging of OBC and streamer data or the decomposition of wide-azimuth data for fracture characterization.

Factorial kriging

Factorial kriging (Matheron, 1982) builds spatial filters based on the decomposition of the variogram or covariance function. It is a linear filtering technique related to Wiener filtering. It has been applied recently to filter nongeological outlier patterns such as directional acquisition imprints on the velocity and the anisotropy parameter (Coléou-2001, Le Meur et al., 2001).

Automatic factorial co-kriging

Factorial co-kriging is used for multivariate datasets. It works with the decomposition of the variogram and cross-variogram models. Coléou (2002) has shown how automatic factorial co-kriging provides spatial filters which yield a decomposition of two sets of data into their common part and their spatially independent residuals without the need for variogram modeling. Given two datasets $Z_1$ and $Z_2$ we define a common part $S$ and spatially independent residuals $R_1$ and $R_2$ by:

$$Z_1 (x) = S (x) + R_1 (x)$$

$$Z_2 (x) = S (x) + R_2 (x).$$

The residuals contain any remaining non-repeatable effects such as acquisition artefacts, random noise and, if present, time-lapse differences. The corresponding covariance functions are $C_1$ and $C_2$:

$$C_1 (h) = C_S (h) + C_{R1} (h)$$

$$C_2 (h) = C_S (h) + C_{R2} (h).$$

For regularly sampled data such as seismic and attributes such as velocities, the values of the experimental variograms are known for all distances h that are relevant to the problem. The covariance of the common part $S$ is given by the experimental cross-variogram. The covariances of the residuals $R_1$ and $R_2$ are given by the differences between the respective experimental variograms and the cross-variogram. This provides a decomposition of the covariance function with no interpretative input and gives an automatic extraction of the common part of two measures using factorial co-kriging. The principle is the same regardless of the dimensionality of the input data.

The following sections show how this technique is being used in seismic processing with a view to improve reservoir characterization. We present results of automatic factorial co-kriging in two and three dimensions, in the time or frequency domain. For the frequency domain application, we can calculate a spatial filter for the amplitude spectrum and for the phase separately. After application of the filters in the frequency domain, we discard the residuals and transform the common frequency components back into the time domain.

Time-lapse application: common velocity cube

A direct application of the common part derived from AFACK is for time-lapse velocity cubes. A 4D processing sequence generally requires a single velocity cube to be applied to the various vintages. The common velocity cube from AFACK is often a better candidate than a cube from one of the surveys and always better than the straight average of the two cubes.

Time-lapse application: repeatability measurement

The geostatistical decomposition of the data into a common part and disjunct partial differences suggests new repeatability measurements. The normalized variograms and the cross-variogram provide a measure of...
spatial repeatability that can be extracted during the stages of a 4D processing sequence where the datasets have a common geometry. The residual variograms (the difference between the variograms and the cross-variogram) show amplitude components not common to both datasets and highlight the direction and strength of the acquisition imprints (Coléou et al., 2002). They can also be used in the design and QC of deterministic filters. The normalized RMS difference (Kragh and Christie, 2001) and the predictability can be applied to measure the distances between the common part and the two inputs or the two residuals. These distances are a measure of the signal-to-noise ratios of the two inputs. An example of this type of analysis is shown in figure 1.

**Time-lapse application: spatial matching filter**

Much effort is applied in time-lapse studies, to isolate a 4D signature from spurious residual energy, which is not related to hydrocarbon production. Global and local matching filters are designed, mainly using least-squares techniques, in order to optimize the subtraction process in areas where no 4D effect is expected and to enhance the production signature in the reservoir area (e.g. Harris, 1998).

Since acquisition artefacts are spatially correlated, we need to use spatial filtering techniques. Whereas deterministic filtering techniques (e.g. Soubaras, 2001) are generally focused on one dataset, the co-kriging technique suggests an alternative statistical filtering which removes noise with uncorrelated spatial components. As with all matching procedures, care has to be taken to create the filter in an area where no 4D effect is expected; this means we have to calculate all variograms using traces well away from the production areas.

**Time-lapse application: 4D signature enhancement**

Equation (1) shows that the 4D difference of two vintages can be recovered from the subtraction of the two residuals $R_1 (x)$ and $R_2 (x)$. It can be advantageous to work with the residuals, called *partial differences*, rather than with the original data, as the 4D effect is easier to see once the common part of the input data has been estimated and subtracted (Coléou et al., 2002). This should allow for a targeted filter design to remove residual noise on the partial differences and a better check of any adverse effect on the time-lapse signature.

**Data reduction applications (stacks, AVO, EI)**

For data reduction processes such as partial or full stack and AVO attributes, consecutive offset filtering reduces random and organised noise pre-stack. The use of the pre-stack redundancy of the data improves the results of all the subsequent data reduction operations. Pre-stack geostatistical filtering produces partial and full stacks with wider spectra and with higher energy. The noise reduction through offsets results in more stable AVO and EI attributes. The Consecutive Offset Factorial Filtering (COFFI) results are illustrated in figure 2 on two gathers from a 3D land acquisition showing severe acquisition imprints. The spatial co-filtering using successive pairs of consecutive offsets reduces the noise so that striping is clearly removed and continuity across offsets is enhanced. In the lower part of the display, the AVA crossplots are displayed for a time sample extracted from each gather. The pre-stack filtering process increases the gradient (left gather in figure 2) and eventually corrects it (right gather in figure 2). Figure 3 shows the effect of this filtering on a cross-line stack section and a post-stack RMS-amplitude map. The stack section is significantly less stripy after filtering and amplitude anomalies are better delineated on the map.

**Data merging of OBC and streamer data**

A growing number of projects require the merging of streamer and OBC data. In this case, we wish to combine two datasets, which represent different measurements of the same geology. This is exactly the model of equation (1). We can therefore use automatic factorial co-kriging applied to post-stack data to create a common cube. Figure 5 shows an example of this technique applied in the frequency domain. Lecerf and Weisser (2003) have also shown that a weak 4D signal can be greatly enhanced by the use of this method.

The previous example has shown how to combine two datasets whose underlying geology is the same. This type of technique has also been successfully applied to surveys whose acquisition is split into two anti-parallel shooting directions.

**Decomposition of wide-azimuth data for fracture characterization**

In seismic fracture characterization (Angerer et al., 2003) we work with azimuth-limited data sets of wide-azimuth, wide-offset surveys which provide the multi-dimensional input to AFACK. Here, geostatistical filtering is performed in two passes and achieves the following: (1) the evaluation of the common part of all azimuths, (2) an isolation of the anisotropy component of each azimuth, and (3) the removal of random and organized noise. Figure 4 shows the decomposition of a synthetic data example. The common part is used as a reference for model building in inversion procedures. The separation of noise and anisotropy components leads to a much more robust determination of fracture parameters since the anisotropic signal is often of a similar order of magnitude as the noise component.
Conclusions

We have presented a brief overview of new applications of geostatistical filtering techniques for seismic processing and specialized problems such as time-lapse analysis, OBC and streamer merging and fracture characterization. The common engine behind all these applications is the automated application of factorial co-kriging, which can be done very efficiently even on large, production-size datasets. The major advantage of AFACK and also the reason for the demonstrated flexibility and widespread applicability of the method is that common parts are extracted automatically without the need for specifying any models of the signal or the noise.

References


Figure 1: Predictability versus NRMS crossplots for (a) top: input datasets; (b) common cube versus vintage 1; (c) common cube versus vintage 2. We see that vintage 1 is closer to the common cube than vintage 2 indicating that it has less noise. All plots are on the same scale.
Pre-stack filtering for AVO and EI

Figure 2: 3D land data example showing the effect on the AVO regressions of consecutive offset factorial filtering (COFFI) of the gathers.

Decomposition of wide-azimuth data for fracture characterization

Figure 4: Result of the automatic factorial co-kriging on one of the azimuth maps. The decomposition shows (a) the original synthetic azimuthal attribute where the polygon delineates the anisotropic part of the map; (b) the common part of all azimuths; (c) the azimuthal anisotropy, and (d) random and organized noise components.

OBC and streamer merge

Figure 5: Surface seismic (left), OBC (middle) and common part (right).

Figure 3: Effect of COFFI on (A) a cross-line stack section and (B) an RMS post-stack map.