M-Factorial Kriging for Seismic Data Noise Attenuation

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Abstract

In the last decade in the petroleum industry, geostatistical filtering solutions based on Factorial Kriging technique have been developed and applied to seismic data sets in various operational contexts. These solutions commonly assume stationarity for the underlying random function, which limits their efficiency as soon as the target area becomes large or involves complex structural patterns.

In this paper we introduce M-Factorial Kriging models, which allow to account for non-stationary effects that are encountered within seismic data sets. In the framework of noise attenuation issues, sources of non-stationarity relate for example to signal absorption, geological structuration, spatial variations of signal-to-noise ratio or varying geometrical features of noise.

M-Factorial Kriging models ensure a better efficiency of the resulting geostatistical filtering process. As a consequence, signal and noise are better separated. This is illustrated by applying M-Factorial Kriging to a noisy PSTM amplitude section.

Introduction

Today, the variogram is at source of many geostatistical models. It enables to build estimation (kriging) and simulation operators by catching the spatial correlation inherent to a data set.

Factorial Kriging is a variogram-based filtering technique developed by Georges Matheron in 1982 [1]. It relies on a simple additive model where the spatial variable under study is modeled by a random function, Z(**x**), which is parted in terms of independent factors:

$$Z(\mathbf{x}) = Z_1(\mathbf{x}) + Z_2(\mathbf{x}) + \ldots$$

Noise attenuation issues can be easily handled into the framework of this model, as far as the noise part of a data set can be considered independent of a complementary signal part:

$$Z(\mathbf{x}) = Z_{NOISE}(\mathbf{x}) + Z_{SIGNAL}(\mathbf{x})$$

In such a way, Factorial Kriging, by estimating $Z_{SIGNAL}(\mathbf{x})$, allows to filter out the noisy component of a data set.

During recent years, geostatistical filtering solutions based on Factorial Kriging technique have been developed and applied to seismic data in various contexts such as data quality control [2], dense seismic velocity regularization [3], acquisition artifacts removal from refraction data [4], 4D repeatability enhancement [5]. Although the technique proves to be efficient for attenuating noise globally, it appears limited when faced with non-stationary phenomena affecting the data.

This paper demonstrates how Moving-GeoStatistics (M-GS) technology, combined with Factorial Kriging technique, provides an optimal way for attenuating noise polluting spatial or spatio-temporal data. The approach, called M-Factorial Kriging, is compared to a conventional Factorial Kriging approach for filtering out the noise of a PSTM amplitude section. The gain in quality is shown.

Why Using Spatially Varying Parameters

In geostatistics, like in signal processing domain, stationary assumptions allow to use a wide range of (stationary) models for processing data. But most of the time, especially for large data sets, these assumptions appear to be defective. Then non-stationary geostatistical models can be selected: let us mention among several, FAI-k models [6], multi-point models [7], or gradual deformation models [8] for example. Unfortunately, these models do not address directly filtering issues.

Conventional Factorial Kriging, as a conventional variogram-based approach, assumes stationarity over the data field for the underlying random function. In such a way, the variogram is considered as invariant whatever the location in the data field. Such invariance is never observed on real data sets when computing some local experimental variograms. **Figure 1a** shows for example a seismic attribute which is locally contaminated by a footprint effect (W-E stripes). **Figure 1b** corresponds to the global experimental variogram, computed from the whole data set, while **Figure 1c** and **Figure 1d** correspond to local experimental variograms computed respectively into two areas, A and B, of equals dimensions. Local variograms differ highly from the global variogram. Moreover, variograms A and B are very different although computed from close data areas. In particular, the signature of the footprint is clearly visible on variogram A (periodic behavior of the N-S direction) but does not appear on variogram B.

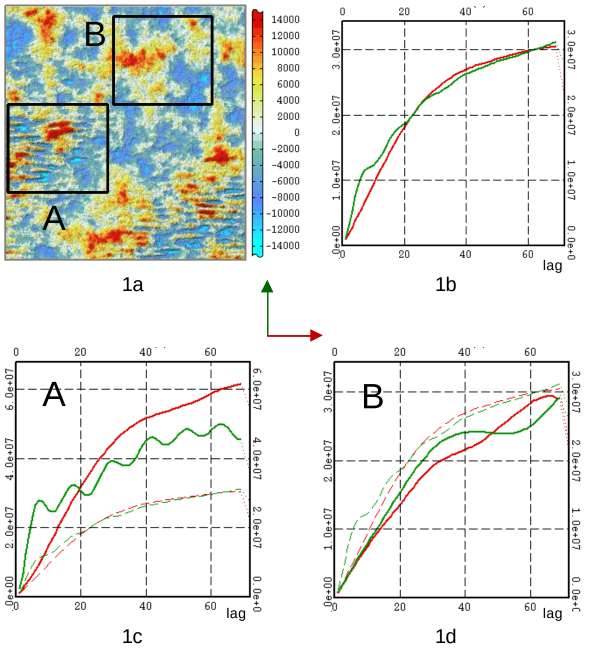


Figure 1

Figure 1a: seismic amplitudes map
Figure 1b: global experimental variogram
Figure 1c: local experimental variogram, area A
Figure 1d: local experimental variogram, area B

This example illustrates the fact that applying conventional Factorial Kriging technique to real data sets may be based on poor fitting of the geostatistical model to the local characteristics of the data. As a consequence unexpected filtering results may occur. The use of spatially varying model parameters makes local adjustment of the Factorial Kriging model possible. Various non-stationary effects can thus be taken into account. As locally adjusted model provides more precise results, filtering results are improved, in particular into the framework of noise attenuation issues.

M-Factorial Kriging

Moving-GeoStatistics (M-GS) is an innovative technology which is fully dedicated to the local optimization of parameters involved in variogram-based models [9], [10]. By optimizing spatially varying model parameters, M-GS guarantees a better adequacy between geostatistical model and data.

There are several approaches to compute such optimized parameters, called M-Parameters. A simple one consists in computing merely local variogram parameters in adjacent areas of the data field and then to interpolate the obtained parameters in order to make them available at every target grid node. More sophisticated algorithms currently under development are based on automatic validation techniques and morphological analysis. They simplify the determination of the M-Parameters and lead to promising results on various real cases that have been tested.

Combined with Factorial Kriging technique, M-GS opens the way to optimal geostatistical filtering of noisy data. Conventional Factorial Kriging approach considers model parameters as constant parameters. On the contrary, M-Factorial Kriging considers model parameters (as well as some computational parameters) as spatially varying parameters which must be optimized.

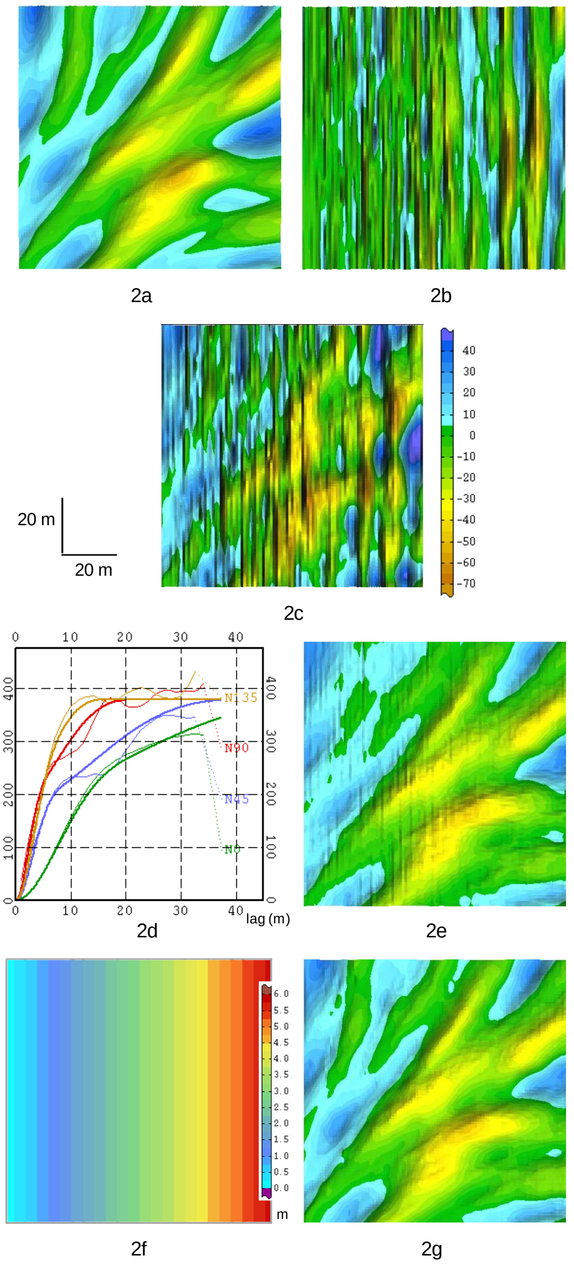


Figure 2

Figure 2a: simulated signal
Figure 2b: simulated noise
Figure 2c: noisy data (simulated signal + simulated noise)
Figure 2d: experimental variogram and variogram model
Figure 2e: estimated signal by conventional Factorial Kriging
Figure 2f: range of the noise structure in X direction
Figure 2g: estimated signal by M-Factorial Kriging

Figure 2 illustrates a comparison between both approaches. Some synthetic data are simulated by a SGS technique using varying structural parameters (**Figure 2a**). We assume that these data correspond to the signal information. In the same way, non-stationary noise is generated (**Figure 2b**). It is composed of vertical stripes of increasing width and variability from the left to the right. The noise is then added to the signal part leading to the noisy data set (**Figure 2c**). Conventional Factorial Kriging and M-Factorial Kriging are tested for filtering out the noise of the noisy data set.

With conventional Factorial Kriging approach, the global experimental variogram is fitted by a variogram model (**Figure 2d**), which is then used for the filtering process. The signal estimated by conventional approach is shown in **Figure 2e**. When comparing it with the original signal (**Figure 2a**), we can notice that some residual noise is still visible on the left part of the image. Moreover some signal structures are not well recovered.

M-Factorial Kriging makes use of locally optimized model parameters. In this example, three main parameters are optimized: the structural orientation of the signal, the noise/signal variability and the range of the noise structure in X direction (**Figure 2f**), which is directly comparable to the width of the stripes. The M-Parameters are introduced into the Factorial Kriging model for filtering the noisy data. The estimated signal is shown in **Figure 2g**. It is well cleared out from the noise. In the meantime the signal is better restored.

As a conclusion, M-Factorial Kriging leads to better noise attenuation and signal preservation by taking into account of local characteristics of the two components, noise and signal, into the geostatistical model.

Noise Attenuation of a PSTM Amplitude Section

Attenuating noise from post-stack seismic amplitudes cubes by geostatistical filtering technique may be complicated because complex types of non-stationarity are often encountered within such data sets: for example, signal absorption, geological structuration, spatial variations of signal-to-noise ratio or varying geometrical features of noise. M-GS models enable to take into account a certain number of these non-stationary effects through M-Parameters determination. As a consequence signal and noise can be better separated.

Figure 3 illustrates a geostatistical noise attenuation process of a noisy PSTM amplitude section. Two noisy structures have been identified: a ~5 CDP structure and a ~1 CDP structure. The last one is highly non-stationary from its intensity content, as its occurs mainly in the top of the section and disappears with depth. These two noisy structures must be removed from the data.

In a first step, a nested variogram model, composed of two noise structure and one signal structure, is fitted to the experimental variogram computed from the whole data set. Based on the variogram model, raw data are then filtered by conventional Factorial Kriging technique. Signal estimation results are displayed together with raw data in a zoom area of the section on **Figure 3a**.

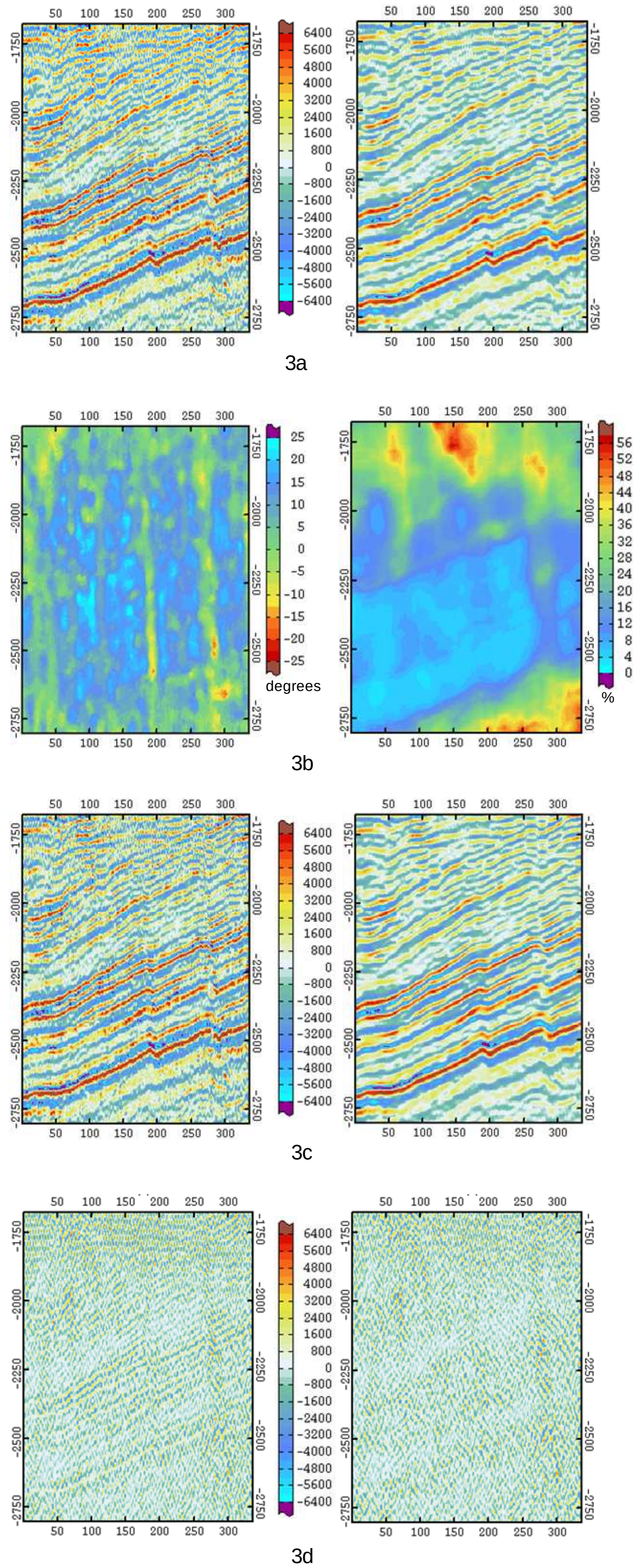
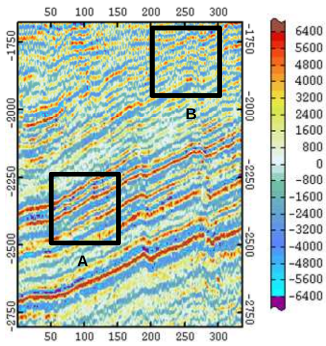


Figure 3

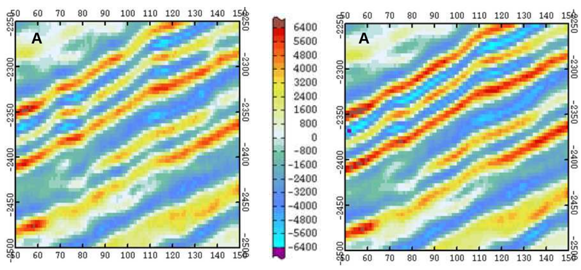
Figure 3a: raw amplitudes and filtered amplitudes (conventional)
Figure 3b: M-Parameters - signal orientation (left), noise % (right)
Figure 3c: raw amplitudes and filtered amplitudes (M-GS)
Figure 3d: extracted noise - conventional (left), M-GS (right)

In a second step, several sensitive parameters of the previous variogram model are optimized, leading to M-Parameters. They correspond to ranges, sills and orientations of the noise and signal structures of the variogram model. For example, the vertical range of the signal, which can be related to the signal resolution, increases with depth in the whole section from 20mstwt to 35mstwt. Two of the M-Parameters are displayed on **Figure 3b**. The first one corresponds to the orientation of the signal structure (degrees in cell units). It can be linked to the geological structuration. The second one corresponds to the amount of noise expressed in % of the total variability of the data. This parameter is highly spatially variable, ranging from 2 to 55%. The most noisy area is located in the northern part of the image around CDP 150.

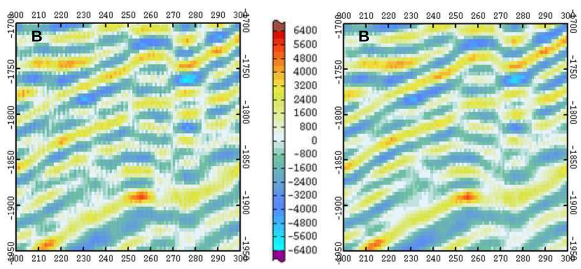
Finally, based on the M-Parameters, M-Factorial Kriging is applied to the raw data for estimating the signal component (**Figure 3c**).



4a



4b



4c

Figure 4

Figure 4a: zoomed areas definition - A and B
Figure 4b: A - filtered amplitudes - conventional (left), M-GS (right)
Figure 4c: B - filtered amplitudes - conventional (left), M-GS (right)

Filtered amplitudes obtained by this optimizing process can be compared to those obtained by conventional Factorial Kriging displayed on **Figure 3b**. The signal is better preserved with M-Factorial Kriging. It is confirmed when looking at the extracted noise (**Figure 3d**): some residual geological information, visible on conventional Factorial Kriging results, is no more visible on M-Factorial Kriging ones. **Figure 4** illustrates this gain in quality on two zoom areas (**Figure 4a**). **Figure 4b** shows that the signal is better restored, while the **Figure 4c** proves that the noisy part of the data is better attenuated.

Conclusions

A proper integration of the structural complexity inherent to any large seismic dataset is required when applying Factorial Kriging for seismic noise attenuation. This integration reduces the risk that the model fits poorly the local data characteristics, leading to unexpected filtering results.

M-Factorial Kriging approach enables to capture non-stationary effects affecting spatial data. This innovative approach, which can be applied on 3D volumes, leads to more precise noise extraction and better signal estimation as it has been shown on a real PSTM amplitude section. The gain in quality may be particularly relevant for seismic processing centered on reservoir objectives preservation.

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