Noise Reduction by M-Factorial Kriging

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Abstract

Factorial Kriging is a classical 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 reduction 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 in the petroleum industry, Factorial Kriging has been extensively applied to seismic data in various noise reduction contexts. Although the technique proved to be efficient for reducing noise globally, it appeared limited when faced with non-stationary phenomena affecting the data.

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

This paper demonstrates how M-GS technology, combined with Factorial Kriging process, provides an optimal way for reducing the noise of a seismic amplitude data set. In particular, it is shown that the M-Factorial Kriging solution, by taking into account of non-stationary effects such as signal absorption, geological structuration, spatial variations of signal-to-noise ratio or varying geometrical features of noise, optimizes noise reduction while preserving signal information. The approach is compared to a conventional factorial kriging approach for filtering out the noise of a PSTM amplitude section. The gain in quality is finally quantified.

Introduction

In geostatistics, the variogram 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, $Z(\mathbf{x})$, 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. Although the technique proves to be efficient for attenuating noise globally, it appears limited when faced with non-stationary phenomena affecting the data.

Moving-GeoStatistics (M-GS) is an innovative technology which is fully dedicated to the local optimization of the parameters of geostatistical models [2], [3]. As a consequence it ensures a better adequacy between geostatistical models and data. M-GS combined with Factorial Kriging technique provides an optimal way for attenuating noise polluting datasets. 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.

M-Factorial Kriging

M-GS models are based on the determination of M-Parameters. M-Parameters are locally optimized versions of structural and computational parameters involved in variogram-based models.

There are several approaches to compute such optimized 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 sophisticate 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, leading to M-Parameters.

Synthetic example

Figure 1 illustrates a comparison between both approaches, conventional Factorial Kriging and M-Factorial Kriging. Some synthetic data are simulated by a SGS technique using varying structural parameters (**Figure 1a**). We assume that these data correspond to the signal information. In the same way, non-stationary noise is generated (**Figure 1b**). 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 1c**). 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 1d**), which is then used for the filtering process. The signal estimated by conventional approach is shown in **Figure 1e**. When comparing it with the original signal (**Figure 1a**), 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 1f**), 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 1g**. 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.

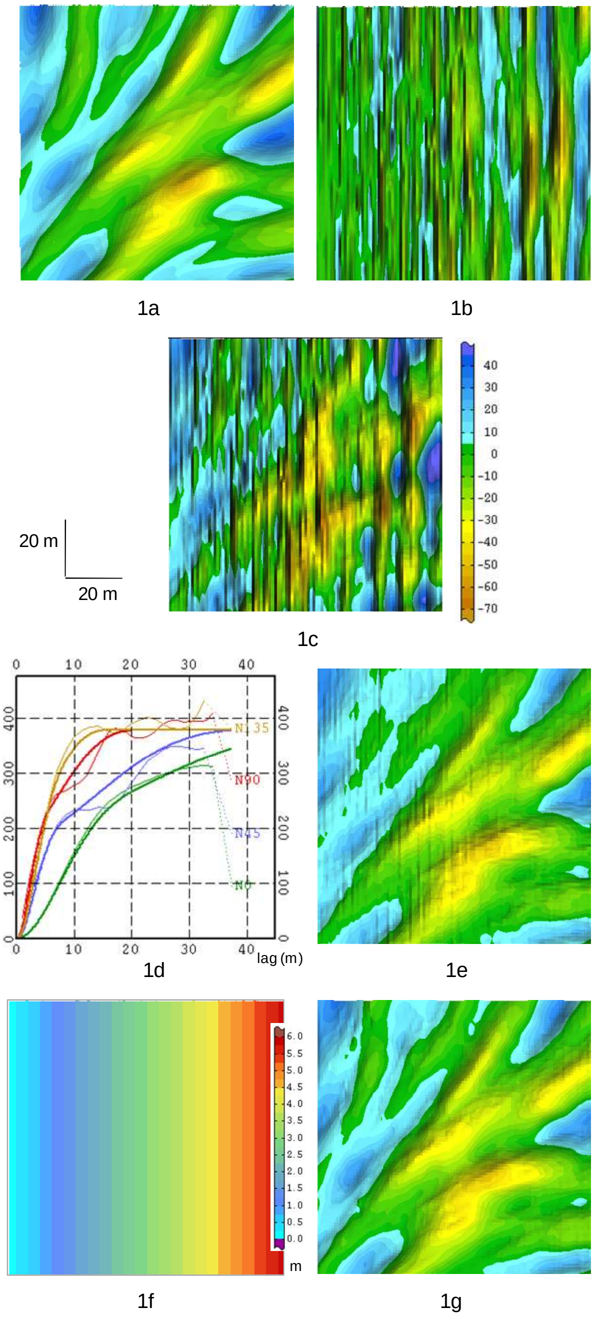

Figure 1

Figure 1a: simulated signal
Figure 1b: simulated noise
Figure 1c: noisy data (simulated signal + simulated noise)
Figure 1d: experimental variogram and variogram model
Figure 1e: estimated signal by conventional Factorial Kriging
Figure 1f: range of the noise structure in X direction
Figure 1g: estimated signal by M-Factorial Kriging

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 such as, 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 discriminated.

Figure 2 illustrates a geostatistical noise attenuation process of a noisy PSTM amplitude section. Two noisy structures have been identified within the section: 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 should 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 2a**.

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 2b**. 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

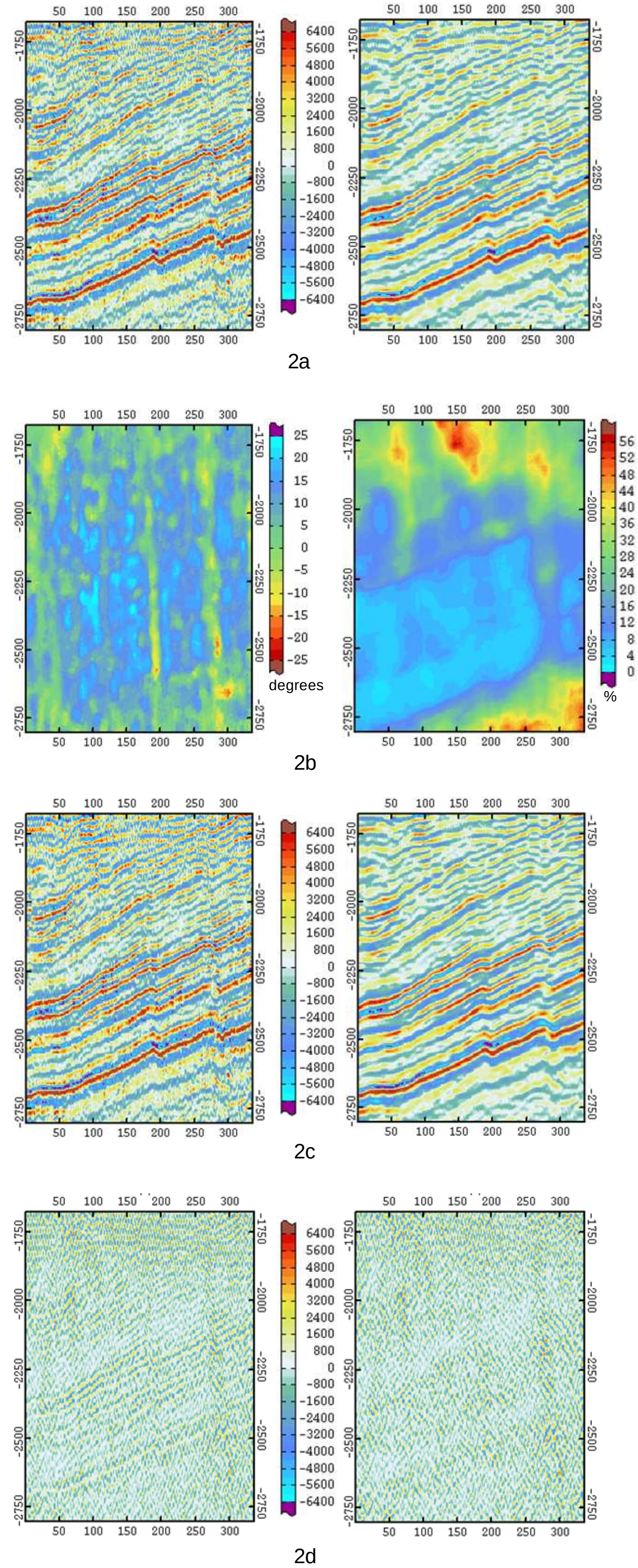

Figure 2

Figure 2a: raw amplitudes and filtered amplitudes (conventional)
Figure 2b: M-Parameters - signal orientation (left), noise % (right)
Figure 2c: raw amplitudes and filtered amplitudes (M-GS)
Figure 2d: extracted noise - conventional (left), M-GS (right)

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 2c**).

Filtered amplitudes obtained by this optimizing process can be compared to those obtained by conventional Factorial Kriging displayed on **Figure 2b**. The signal is better preserved with M-Factorial Kriging. It is confirmed when looking at the extracted noise (**Figure 2d**): some residual geological information, visible on conventional Factorial Kriging results, is no more visible on M-Factorial Kriging ones. **Figure 3** illustrates this gain in quality on two closer zoom areas (**Figure 3a**). Regarding M-Factorial Kriging results, **Figure 3b** shows that the signal is better restored, while the **Figure 3c** proves that the noisy part of the data is better attenuated.

This seismic amplitudes denoising example demonstrates how M-Factorial Kriging applied to real data can be successful. M-parameters enable to capture the structural complexity of the data better than a conventional (global) approach do. Logically, better adjusted model leads to better filtering results.

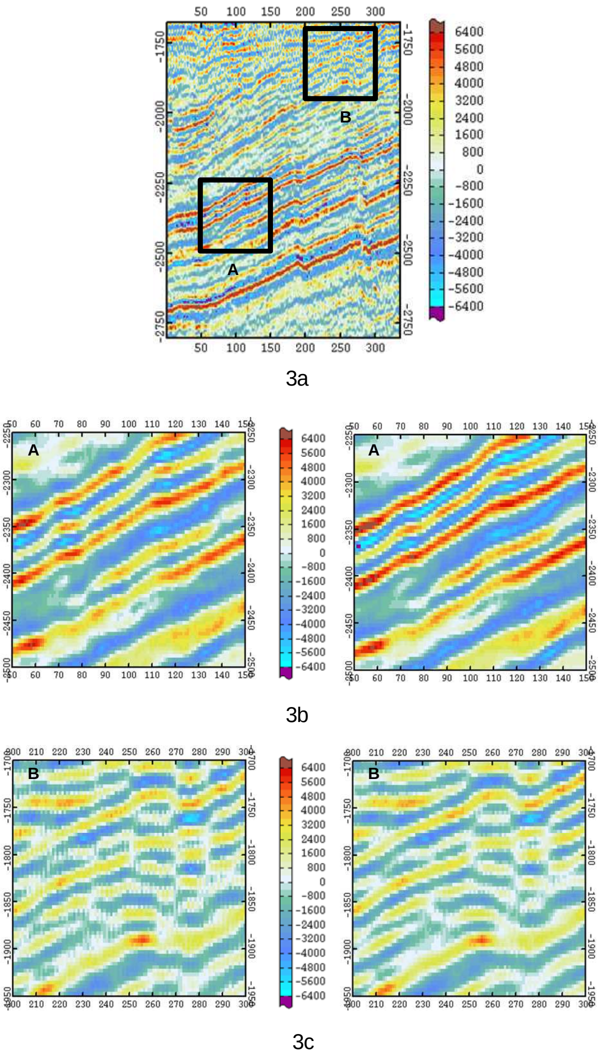

Figure 3

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)

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. Applied to seismic 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.

More generally, M-Factorial Kriging is a high precision filtering technique which can be used in various spatial data separation contexts.

References

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