Introduction

Geostatistics provides probabilistic models and related tools to analyse and process spatially distributed data in various domains: mines, climatology, soil science, hydrogeology, public health, etc. Nowadays geostatistical solutions are widely used in the petroleum industry, especially for data integration in earth models [1]. More recently geostatistics has been applied in some stages of seismic processing. As mentioned in [1], the majority of the geostatistical models used in the petroleum industry are variogram-based models. The variogram enables to build stable and effective estimation (kriging) and simulation operators by catching the mean spatial correlation inherent to a data set. Despite their popularity, variogram-based models are the subject of several criticisms. The main one is formulated in [2] within the framework of reservoir modeling: “the variogram is only a very limited measure or means of quantification of actual spatial patterns occurring in the reservoir.” In other words, variogram-based models should not be able to reproduce precisely the structural complexity of the reality. To overcome this, alternative geostatistical models have been developed, such as multi-point [2] and gradual deformation [3] models, for example. However, these models concern mainly simulation issues and may be seen as less comprehensive than standard variogram-based models.

In this paper, we present new geostatistical models, called M-GS models**,** which allow to capture better the structural complexity of spatial data sets. They are based on an optimized determination of structural and computational parameters. As M-GS models are variogram-based models, they address whatever spatial estimation or simulation issues. They lead to more precise and/or more realistic estimation and simulation results than conventional variogram-based models. It is shown by four examples regarding gridding (2), noise removal and simulation issues.

M-GS models

Variogram-based models - Structural and computational parameters

To be applied, variogram-based models generally require a 2-steps tuning phase called structural analysis (or variographic analysis). The first step consists in interpreting the experimental variogram(s) computed from the data. This step is rather likely to involve the user’s knowledge about his data set. Based on the first step conclusions, the second step aims at fitting a single or a set of parameterized functions to the experimental variogram, thus defining a variogram model. We call structural parameters the parameters which are related to the variogram model such as ranges, sill(s), anisotropy coefficient(s), etc.

In order to run variogram-based estimation and simulation algorithms, other parameters must be tuned. They form the computational parameters category. They are mainly related to the neighbourhood used for selecting data points surrounding the target point (the point which is estimated or simulated). In practice, the computational parameters are often utilized for managing processing times, specifically when dealing with large data sets.

Variogram-based estimation and simulation models are sensible to the structural and computational parameters. Though sensibility may be highly variable depending on some data set characteristics (sampling density, variable continuity, etc.), it is rarely null. When facing with a spatial estimation or simulation problem, one must pay careful attention not only to the choice of the right geostatistical model, but also to the tuning of the associated parameters. This is particularly relevant when dealing with variogram-based models.

M-GS principle and main advantages

M-GS (M-GeoStatistics) is a technology[1] which is fully dedicated to the optimization of the parameters of variogram-based models. M-GS considers the structural and computational

[1] Patent recording.

parameters as a set of dependant parameters to be spatially optimized. The optimization process, which may be guided by objective criteria or subjective criteria, is carried out during a M-structural analysis phase that leads to a set of spatially variable structural and computational parameters (M-parameters).

M-GS ensures a better adequacy between the geostatistical model and the data. In consequence, spatial estimation and simulation results are more precise than those obtained with conventional variogram-based models. Moreover this technology opens the way to new geostatistical mapping/gridding (even simulating) practices by allowing the user to introduce his structural knowledge about the data field directly into the spatial estimation model. In that way geostatistical mapping/gridding by kriging techniques is no more a variogram guided process aiming at generating the most probable map/grid, but a human process aiming at generating the most probable desired map/grid.

M-GS application examples

Optimized mapping of a seismic attribute by M-ordinary kriging - ***Figure 1***

In the petroleum industry, gridding irregularly sampled data is a common operation. This example concerns the mapping of 2D data points, which have been extracted from a seismic residual velocity cube (**Figure 1.a**). Conventional ordinary kriging and M-ordinary kriging techniques are used. Velocity residuals maps as well as derived uncertainty maps are compared.

A conventional structural analysis is performed in order to determine a consistent variogram model. The experimental variogram is fitted by the following isotropic variogram model: cubic function, range of 14 CDP, sill of 87. A M-structural analysis, driven in an isotropic and single function context, is applied to the same data set. M-parameters are generated. One of them, the M-range, presents strong variations, ranging from 6 to 27 CDP over the data field.

Ordinary kriging, using the cubic model of 14 CDP, and M-ordinary kriging, using the M-parameters, are carried out for mapping the seismic attribute. Both generated velocity residuals maps (**Figure 1.b**) show important differences in the north-eastern part of the field (locally up to 40%). A cross-validation computation in that area reveals that the M-GS map is on average 20% more precise than the conventional kriging map.

One of the advantages of kriging techniques is that they produce uncertainty maps associated to the estimation process. Uncertainties corresponding to conventional ordinary krigring and to M-ordinary kriging are expressed in terms of (kriging) standard deviation maps (**Figure 1.c**). As major differences are observed over the field, operational conclusions based on each map should be probably different. In particular the M-GS uncertainty map brings out a high uncertainty area (North-East) which is not detected on the conventional uncertainty map.

Channel realistic mapping by M-ordinary kriging (synthetic example) - ***Figure 2***

In this example, 40 data points have been simulated in order to illustrate a guided mapping process by M-ordinary kriging technique. These data points could represent topographic information, for example.

Following a conventional structural analysis, a depth map is generated by ordinary kriging (**Figure 2.a**). This map, based on a statistical analysis, is meant to be objective. In a second step, we would like to introduce into the estimation model a priori information corresponding to the user's structural knowledge. It could correspond, for example, to the interpretation of a channel pattern (**Figure 2.a**, dashed line). For integrating this information, reliable M-parameters are computed. Afterwards, they are used into a M-ordinary kriging process to produce the map displayed in **Figure 2.b**. The channel information has been transcribed into the M-GS model and well delivered into the map.

Optimized footprint removal by M-factorial kriging - ***Figure 3***

Recently geostatistical filtering by factorial kriging technique has been applied successfully to seismic data in noise reduction or quality check operational contexts as shown in [4], [5], [6], and [7].

Figure 3.a displays a seismic amplitude map, which is affected by a footprint effect. The footprint is apparent only on two areas of the field. The aim is to filter it out within the contaminated areas while preserving fully the non-contaminated areas. In such cases conventional factorial kriging is not recommended because it acts on the whole data field.

A M-structural analysis is launched using a two-functions variogram model: a spherical function for the signal and a sinus cardinal function for the footprint effect. The generated M-parameters are used to filter the amplitude map by M-factorial kriging. The resulting filtered amplitude map is well cleared out from the footprint (**Figure 3.b**). In the meantime the signal resolution is fully preserved. In non-contaminated areas, amplitudes have not been modified. This can be checked out on the extracted footprint map (**Figure 3.c**).

Simulations by M-SGS (synthetic example) - ***Figure 4***

Geostatistical simulations using conventional variogram-based models are often the subject of criticisms. The major one is about their inability to reproduce realistic patterns. M-GS simulation models overcome this shortcoming by enabling to reproduce a wide range of complex patterns.

In **Figure 4** there are presented three types of simulations corresponding to three kinds of M-parameters sets. The simulations, which are conditioned to 20 data points, have been obtained by a M-SGS (M-Sequential Gaussian Simulation) process. They reproduce some patterns that can not be reached by conventional variogram-based simulation models. Please note that they have exact statistical and spatial properties.

Conclusion

M-GS models enable to capture better the structural complexity of spatially distributed data by considering the structural and computational parameters of variogram-based models as a set of dependant parameters to be spatially optimized. Consequently estimation and simulation results are more precise and/or more realistic than those obtained with conventional variogram-based models.

As M-GS algorithms are based on existing variogram-based algorithms and in most cases do not increase computation time (excepted for the filtering of large data cubes), many M-GS applications are expected in near future in various domains.

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Figure 1 *- Optimized mapping of a seismic attribute by M-ordinary kriging*

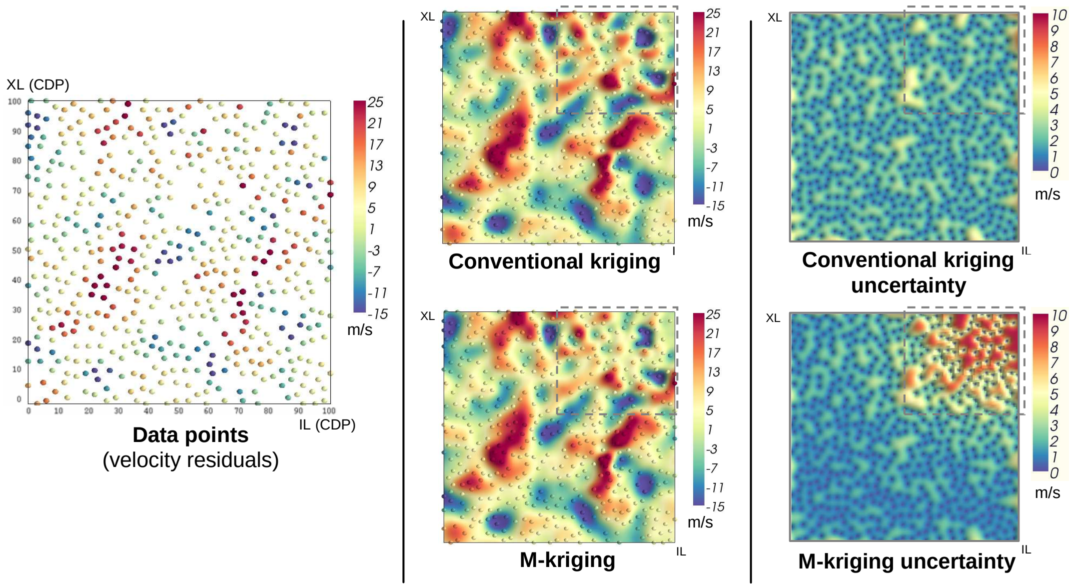

Figure 1.a ***Figure 1.b*** ***Figure 1.c***

Figure 2 *- Channel realistic mapping by M-ordinary kriging*

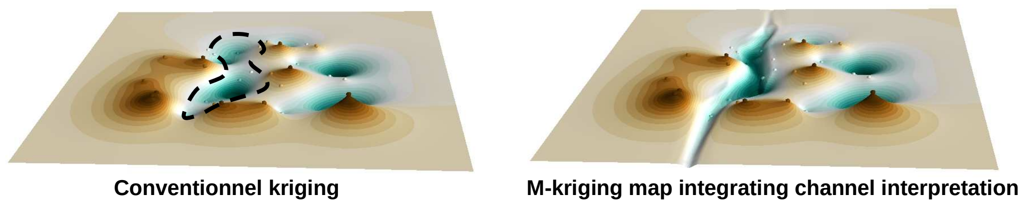

Figure 2.a ***Figure 2.b***

Figure 3 *– Optimized footprint removal by M-factorial kriging*

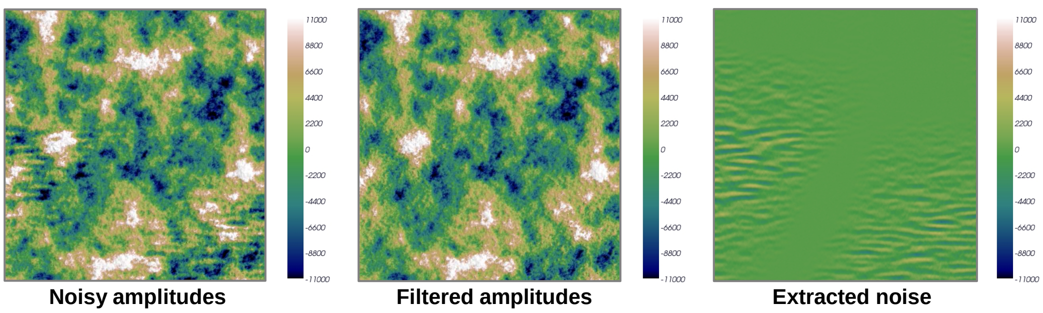

Figure 3.a ***Figure 3.b*** ***Figure 3.c***

Figure 4 *– Examples of simulations by M-SGS*