Using Blast Data to infer Training Images for MPS Simulation of Continuous Variables

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Multiple-point simulation (MPS) methods have been developed over the past decade to reproduce complex geological models for categorical variables. However, there is less work exploring the use of MPS techniques for continuous variables, specifically for use in the mining industry. This paper deals with using blast hole data as training images (TI) for MPS simulation. Normally, information from blast-hole data contains significant error. Using blast hole data in MPS simulation may introduce unwanted error. To apply MPS simulation using blast hole data as a TI, the reduction of error in sampling must be considered. To do this, the data will be averaged up to a volume where the error is negligible. At this scale, it would be appropriate to consider the data as a TI. The appropriate scale for considering the data as a TI depends on the level of error in the samples.

Introduction

Multiple-point simulation (MPS) methods have been developed over the past decade to reproduce complex geological models. Currently, there are many algorithms for MPS simulation when the variables of interest are categorical. For continuous variables, filter based simulation, or FILTERSIM (Zhang et al., 2006; Wu et al., 2008) and direct sampling algorithms proposed by Mariethoz et al (2010) are available. One source for continuous variable training images (TI) in the mining industry are blast hole data. These nearly exhaustive databases could be used as TIs in MPS simulation. Unfortunately, information from blast-hole data typically contains high levels of errors. Therefore, using these data for TIs in MPS simulation may cause inaccurate results. One solution would be to average BH data together until the errors are negligible. At this larger scale, BH data could be used as a TI.

Literature review

Multipoint Simulation Methods & TI for Mining: MPS methods have been developed over the past decade to reproduce complex geological models. Templates are scanned over the TI to assess the local conditional distribution at an unsampled location in the realization. The local conditional distribution is entirely calculated based on the reoccurrence of the particular pattern of nearby condition data in the TI. Currently, there are many categorical variable algorithms which are available to implement MPS (Guardiano and Srivastava, 1993; Strebelle, 2002 to name a few).

MPS can be applied to the simulation of continuous variables. One of the MPS methods is FILTERSIM (Zhang, 2006; Wu et al. 2008). The method is an MPS simulation method that associates filter scores to patterns; it works with both categorical and continuous training images. FILTERSIM consists of three main steps, filter score calculation, pattern classification and pattern simulation. A set of mathematical functions called filters is applied to the training image. The training images are scanned using a template configuration. Each training image's pattern has a set of filter scores. Another MPS method applying for continuous variables is the direct sampling algorithm proposed by Mariethoz et al (2010).

Sample Errors: The fundamental cause of sampling errors in rocks and minerals is well understood (Gy, 1982; Francois-Bongarcon, 1993; Pitard, 1993 to name a few). The errors in sampling depend on several factors including the following (Marat Abzalov).

- The chosen sample extraction and preparation procedure, referred as sampling protocol. The main error of this type is known as Fundamental Sampling Error (Gy, 1982). It is always present and cannot be fully eliminated as it is related to intrinsic characteristics of the sampled material, such as mineralogy and texture of mineralization. The Fundamental Sampling Error (FSE) can be minimized through optimization of the sampling protocols. The first group also includes Grouping- Segregation error which is a consequence of the distribution heterogeneity of the sampled material (Pitard, 1993) and therefore this error also relates to the intrinsic characteristics of the sampled material.
- The errors depend on how rigorously the sampling protocol was developed, implemented and followed. The group includes delimitation, extraction, preparation and weighing errors. These errors are caused by incorrect extraction of the samples from a lot, their suboptimal preparation procedures, contamination and incorrect measurements. Human errors, such as mixed sample numbers, can also be included in this group. These types of errors can be minimized by upgrading practices of the samples extraction and

preparation, which usually needs an improvement of the quality control procedures and often requires equipment upgrading.

- Analytical and instrumental errors occur during the analytical operations (Gy, 1982). The group includes assaying, moisture analysis, weighing of the aliquots, density analysis, precision errors and bias caused by suboptimal performance of analytical instruments.

All these sources of error lead to blast holes samples that can have a significant level of error. We will assume that this error is unbiased, comprised of all above sources, and follows a known distribution.

Implementation

In order to assess the effect of BH samples on MPS, first assume that the blast-hole sampling errors are normally distributed or uniform distributed. Different testing cases (Table 1) are conducted for different scales to block average to. The implementation steps are:

1. Build a synthetic model: this step is performed to generate a 3D model using sequential Gaussian simulation and rock type data from a selected training image.
2. The model will be sampled at each drill-hole location to get synthetic blasting-hole samples. Errors are then added following a normal or uniform distribution.
3. For different scales, the mean squared error between truth values (grade) and blast-hole samples values (grade) are extracted to find the optimal scale with acceptable blast hole error.

To illustrate the practical implementation of the above procedures the following synthetic example has been prepared. Consider a domain of 115x128x11 with the exhaustive data shown in Figure 1a. Outside the ore body the grade is normally distributed with a mean of 2 g/t and standard deviation of 0.5 g/t. The vein has a mean grade of 100 g/t and standard deviation of 20 g/t following a lognormal distribution. SGS is then applied to generate the exhaustive truth model (Figure 1). Grade values at blast-hole sample locations in the 3D exhaustive model are extracted and used as data for the analysis. Random errors are added to the BH data which are assumed to be uniformly or normally distributed. In order to compare the results from the truth grade with the blast-hole samples grade, consider an available dataset with 115x128 sample locations (Figure 2) placed over a regular grid of 115×128. The sampling errors are assigned a uniform distribution form -20% to 20% or a normal distribution. By performing the averaging for a different number of blast holes, the appropriate scale for particular error levels and distributions can be determined (Figure 3).

Table 1. Test cases.

Parameters	BASED CASE	Tested Cases						
BH sampling Error	**20 %**	10%	15%	20%	25%	30%	35%	40%
Range	**a x BH Spacing**	5a	10a	15a	20a	25a	30a	40a
Grade Distribution	**Normal**	Normal			Log-Normal			
Errors models	**Normal**	Uniform -20% , +20%			Normal, μ =0, σ^2=200			

To measure the effect of BH-sampling errors, the 3D model is created by assuming that grade distribution is uniform. By performing as the following above steps, the results are shown in Figure 3 which presents the summary of Mean Square Errors (MSE) for different BH upscaling. It can be seen (Figure 3) that there is a significant reduction in MSE when the averaging increases from 2 units to 4 units. Note that an averaging of '2' indicates that a 2x2 pattern of BH samples was averaged into a single value, a total of 4 BH samples. The MSE stabilizes quickly. Regarding the effect of variogram ranges for the underlying variable, ore-body distribution models and BH error models Figures 4, 5 and 6 summarize the results. In general, the largest effect on the appropriate number of BH samples to average is a result of the initial sampling error level. It is recommended that for most configurations and error levels, a 3x3 pattern of BH sample be averaged to generate a reasonable TI for use in MPS.

Conclusion and future work

This work deals with the selection of appropriate BH spacing sizes to reduce the effect of blast-hole sample errors, grade distributed models, ranges, and errors distributed models when using BH data for MPS TI's. By choosing the optimal block scale, blast-hole errors will become insignificant when used as a TI for MPS simulation. BH data should be averaged to at least 3x3 (9 BH samples) or up to 5x5 (25 BH samples) in some cases for acceptable error reduction.

References

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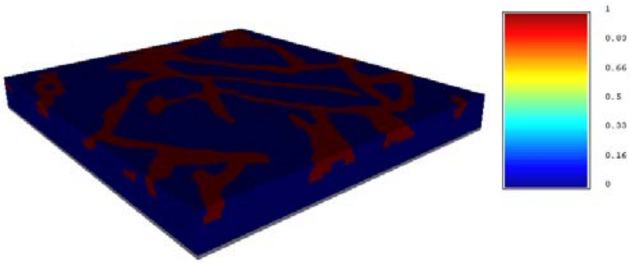
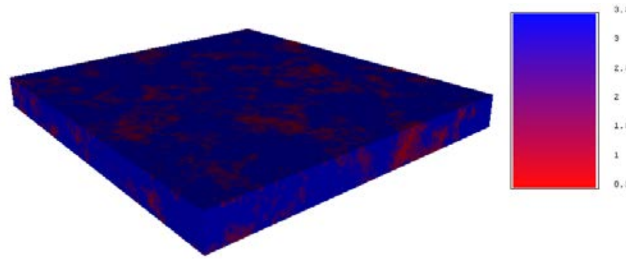
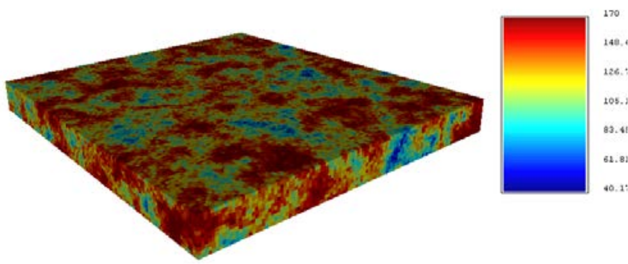


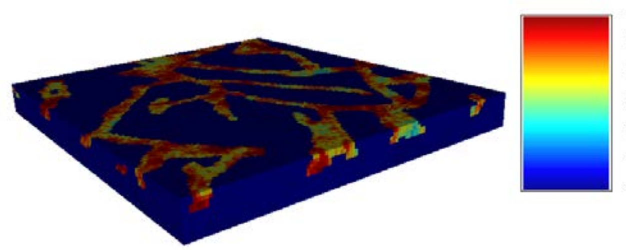
a. TIs



b. Outside of the vein
(mean =2 g/t, SD =0.5 g/t)



c. Inside of the vein
(mean =100 g/t, SD =20 g/t)



d. Merge-Model

Figure 1. Illustration of main steps to convert categorical variables to continuous variables using Sequential Gaussian Simulation (SGS)

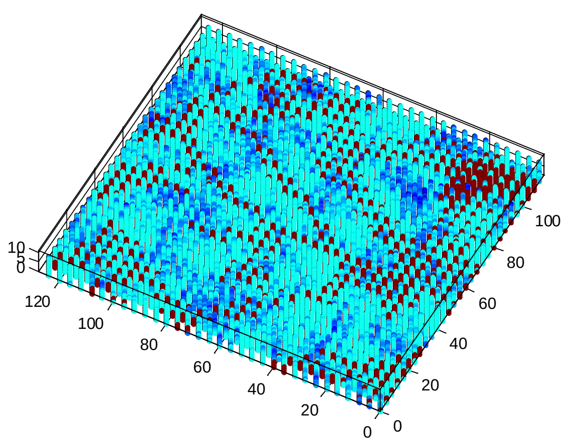


Figure 2: Blast-hole Sampling location

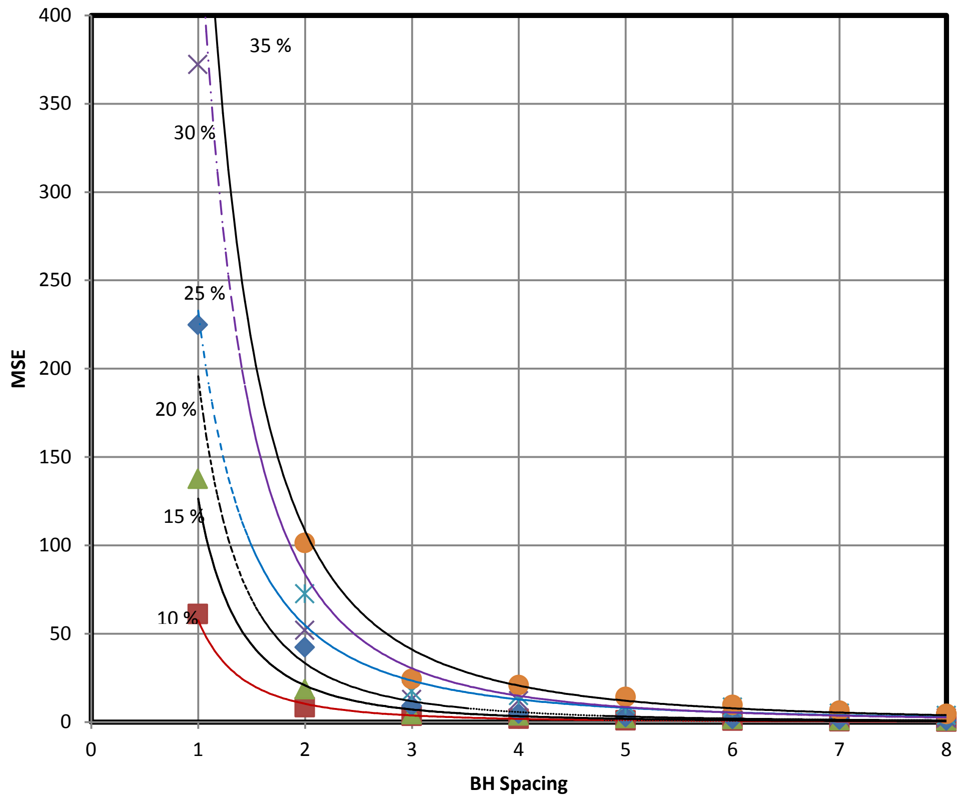


Figure 3. Relationship between MSE and Block Sizes & Errors (%)

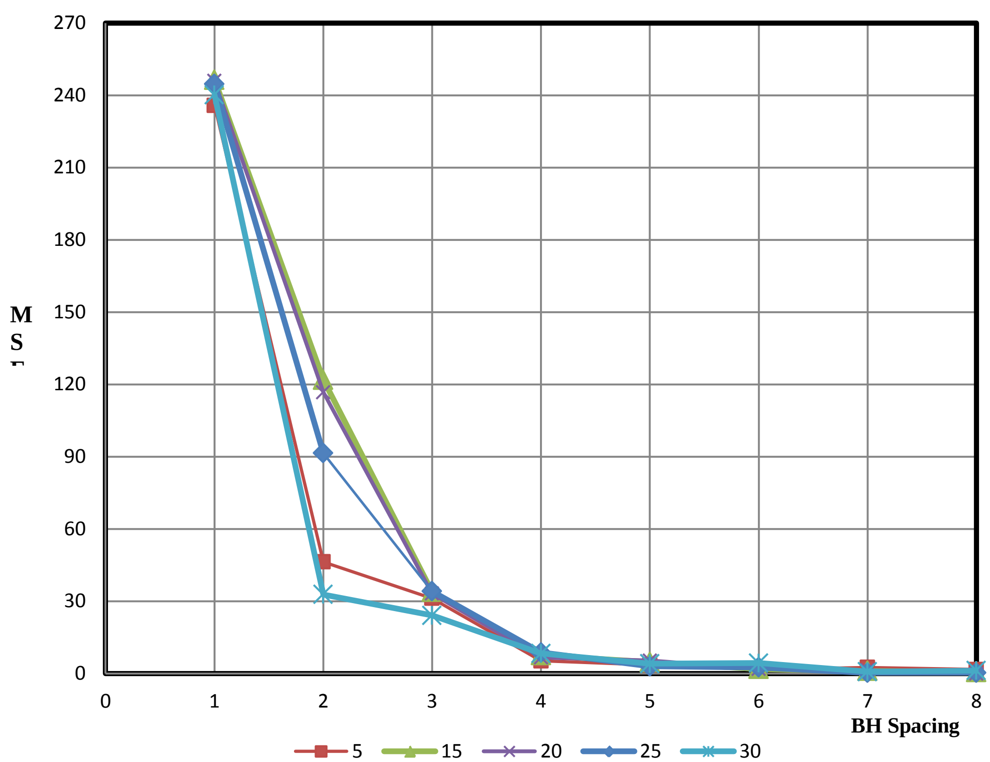


Figure 4. MSE versus BH spacing for different ranges (a)

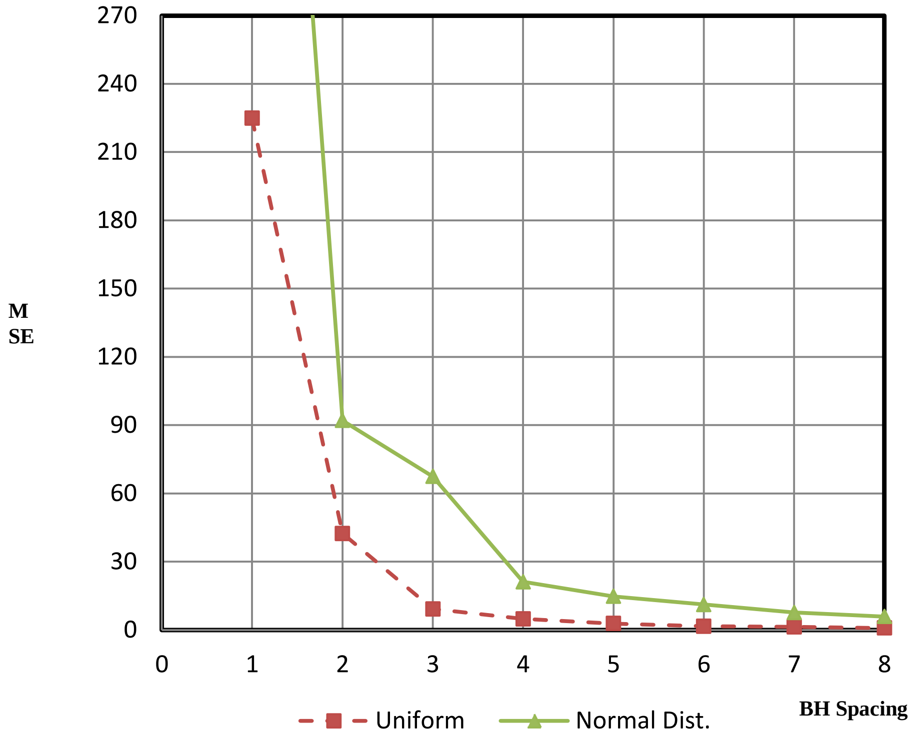


Figure 5. MSE vs BH spacing for different ore-body distributed models

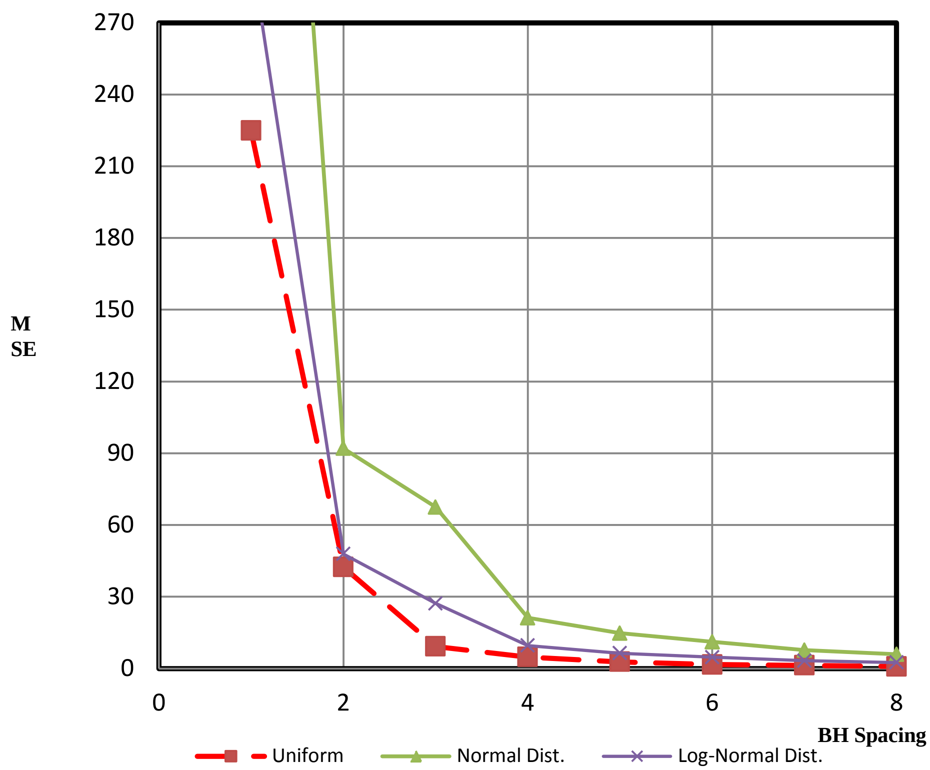


Figure 6. MSE vs BH spacing for different BH-errors models