Another Look at Realization Cleaning

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Cell based simulation is a commonly used method for categorical variable simulation. Although the method has several advantages such as honoring conditioning data and easiness of application, the resulting models often present unrealistic short scale variations. The short scale variability could be noise due to the simulation process and it may have an impact on the flow simulation. Removing and cleaning those short scale variabilities is required. Previously, the MAPS algorithm was proposed. In this work, the MAPS algorithm is modified to find optimal cleaning weights and window sizes. The presented method preserves the spatial heterogeneity (variogram or multiple-point distribution) during cleaning.

1. Introduction

There are two main approaches in reservoir facies modeling: object-based and pixel-based. The object-based approach parametrically models objects that have different geometries and dimensions and introduces the objects in the reservoir. Pixel-based approaches assign facies on a cell-by-cell basis statistically correlated with data and other cells. Pixel-based approachs are widely used to model reservoir facies. Sequential indicator simulation is a commonly used technique for several reasons: (1) exact reproduction of conditioning data, (2) control over the spatial statistical properties of the variable of interest, (3) easiness to account for soft data. Pixel-based methods are preferentially selected when there is no clear understanding of the depositional environment.

As addressed by Deutsch (1998), pixel-based facies realizations have several concerns such as the presence of short scale noisy variations and often poor reproduction of input proportions. Poor reproduction of input proportions is caused by the necessary order relations correction in sequential indicator simulation. Post-processing is often useful for ensuring input proportions. An efficient cleaning categorical variable algorithm and program was developed by Deutsch. The method is based on generating the facies at each cell that maximizes a-posteriori probability (MAPS). A posteriori probability is calculated using facies realization within the limited neighborhood (e.g. 3x3x1 in 2D modeling and 3x3x3 in 3D modeling) centered about the cell location being considered. Different weights can be applied based on the closeness to the centre; the central location has higher weight and peripheral locations have lower weights. The main concern of the MAPS algorithm was how to select weights and the size of the weighting window. The cleaning process affects the heterogeneity of the model (Figure 1). The modified MAPS program gives two options for selecting weights: covariance based weights and iteratively optimized weights. The first option accounts for the input variogram (spatial anisotropy). This option may be desirable in terms of accounting for spatial continuity, however, the degree of cleanness is still an issue. The second option for weighting is based on the multiple-point histograms. A smooth Gaussian function is fixed as a weighting function, but the slope of the Gaussian function is optimized with the reference multiple-point histograms.

2. Consequence of Cleaning Short Scale Variability

Short scale variability is sometimes treated as unwanted noise, but it is treated as a critical feature in some cases. The decision should be based on the purpose of modeling, limit of modeling area and so on. Figure 2 shows a result of SISIM and its cleaned version using 5x5 local cleaning window. Large scale heterogeneity of the realization becomes significant in the cleaned realization, and small scale variability is reduced because isolated facies codes are merged into the most likelihood facies code in the neighborhood. The smoothness is critically affected by the choice of local window size and weights, and consequentially the smoothness affects flow simulation results.

The correct way to check the effect of realization cleaning is to run a flow simulation on a number of realizations that have various degree of cleaning. Practically, the full multivariate character can be assessed by comparing the multiple point distribution. Four point histograms of realizations shown in Figure 1 are shown in Figure 2. Homogeneous realizations has more uniformly distributed multiple point histograms and heterogeneous realizations (cleaned image) typically have a bimodal histogram. A classical entropy is calculated for the multiple-point histograms; bimodal histogram has lower entropy than the uniform histogram. The entropy of multiple-point histograms will be used as an objective function to find optimal cleaning weights.

3. Methods for Realization Cleaning

Two cleaning methods are investigated: kriging based method and multiple-point histogram based method. The kriging based method is to account for spatial continuity when cleaning the realization. Once the size of a local window is chosen, the kriging weights are assigned to the cells in the window. Multiple-point histogram based method is an iterative method. In this method, Gaussian function is fixed as a weighting function. Iteration is done to find the slope of Gaussian function.

Kriging based weights

Indicator kriging estimates are used for weights in the modified MAPS. There are some desirable aspects of using kriging results; (1) spatial continuity is still preserved in the cleaned image, (2) weights are different for different facies, (3) conditioning data can be straightforwardly weighted (e.g. weight is 1 at conditioning data and otherwise, weight is 0). The updated local conditional probability $q_k(\mathbf{u})$ is calculated by;

$$q_k(\mathbf{u}) = \frac{1}{S} \sum_{\mathbf{u}' \in W(\mathbf{u})} w(\mathbf{u}') \frac{p_k^{\text{target}}(\mathbf{u})}{p_k^{(0)}(\mathbf{u})} i_k^{(0)}(\mathbf{u}') \tag{1}$$

where S is a normalizing constant, $W(\mathbf{u})$ is a local window centered at $\mathbf{u}$, $w(\mathbf{u}')$ is a weight and it is taken from indicator kriging result, $p_k^{\text{target}}(\mathbf{u})$ is a global proportion of k, $p_k^{(0)}(\mathbf{u})$ is a calculated proportion of realization.

Multiple-point Histogram based Weights

Multiple-point histogram is a reasonable measure of spatial heterogeneity of geologic models. The main idea of the multiple-point histogram based weight is that: (1) generate pixel-based facies realizations (SISIM), (2) calculate multiple-point histograms and their entropy measure for each realizations, (3) calculate multiple-point histogram and its entropy from the reference image (e.g. TIs), and (4) optimize the slope of weighting function until the entropy difference becomes smaller. The optimized weights are input into equation (1) to generate cleaned realization.

4. Examples

Kriging based cleaning weights are tested first. Results from the indicator kriging (ik3d.out) should be required. This method assigns the maximum weight at the conditioning data location (kriging vale = 1) and thus, conditioning data is honored. The arbitrary user input weights and kriging based weight schemes are compared in Figure 3. 3x3 window is used for both method. The original uncleaned image is generated using anisotropic variograms (top in Figure 3).

	Facies 1	Facies 2	Facies 3
Anisotropic direction	0	40 degrees (NE)	120 degrees (SE)

Cleaned realizations are shown in the bottom in Figure 3. Two images look similar in terms of cleanness and both exactly reproduced input global proportions. Removing short scale variability, however, leads to different spatial heterogeneity. For example, experimental variograms are reproduced from the cleaned realizations and they are drawn in Figure 4. Facies 2 and 3 have directional anisotropy, so variogram reproduction is checked for the facies 2 and 3. Cleaning with isotropic user input weights generate more smooth realization within short distance at major continuity direction. This result is very natural; cleaning removes short scale variation and make the realization more continuous. However, it does not honor the anisotropic input variogram. Kriging weight based method reasonably reproduced the input variogram at the major continuity direction (right column in Figure 4)

Multiple-point histogram based weights are applied. The first result is to find the optimal cleaning weight using the fixed window size (3-by-3 in this example), and the second result is to find the optimal cleaning window size in addition to the weights. Four point histograms are calculated and their entropy are used as an objective function. Any multiple-point histograms can be used as an objective function. The optimized weight values are input the cleaning equation in Eq. (1). The cleaned image appears quite similar to the reference TI. The entropy is almost identical.

9. Conclusions

The motivation for cleaning categorical facies realizations is practical. Isolated facies realization make facies model unrealistic in terms of geologic context. MAPS algorithm is to update isolated cells based on the neighborhood facies realization. The main drawback is to the selection of optimal weight and window size. Moreover, the cleaning process should not destruct the spatial heterogeneity for the sake of clean image.

In this work, kriging weight based and multiple-point histogram based cleaning weights are discussed. Kriging based method do not destruct the input variograms. However, the cleaning window size is till input. Multiple-point histogram based method is more flexible. This method requires the reference image such as TIs to calculate multiple-point histograms. The cleaning weights and window size are optimized based on the entropy differences. Examples show that the approach appears flexible in its ability to clean realizations.

References

Deutsch, C.V., 1998, Cleaning categorical variable(lithofacies) realizations with maximum a-posteriori selection , *Computers & Geosciences* 24, 551-562.

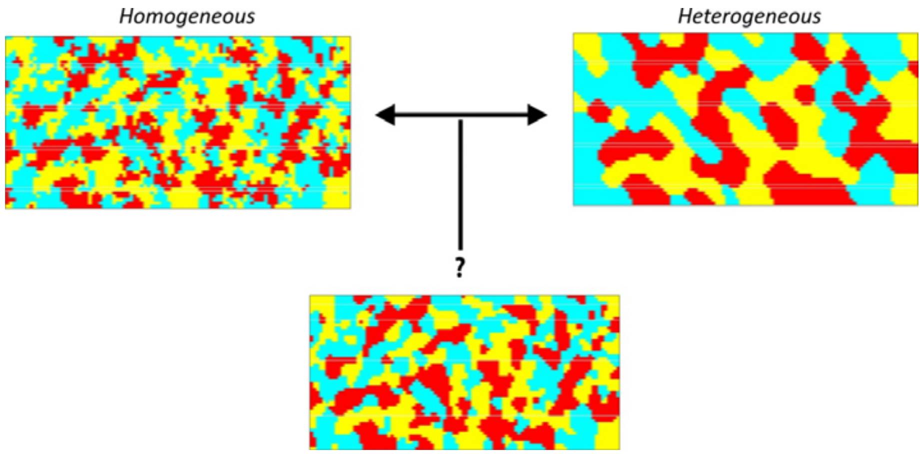

Figure 1: Change of heterogeneity by realization cleaning.

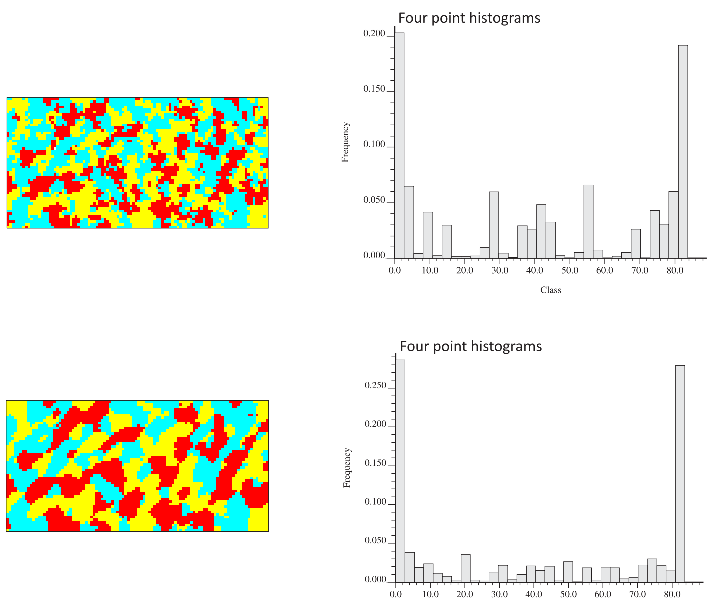

Figure 2: A consequence of realization cleaning. Multivariate feature is changed by removing short scale variation

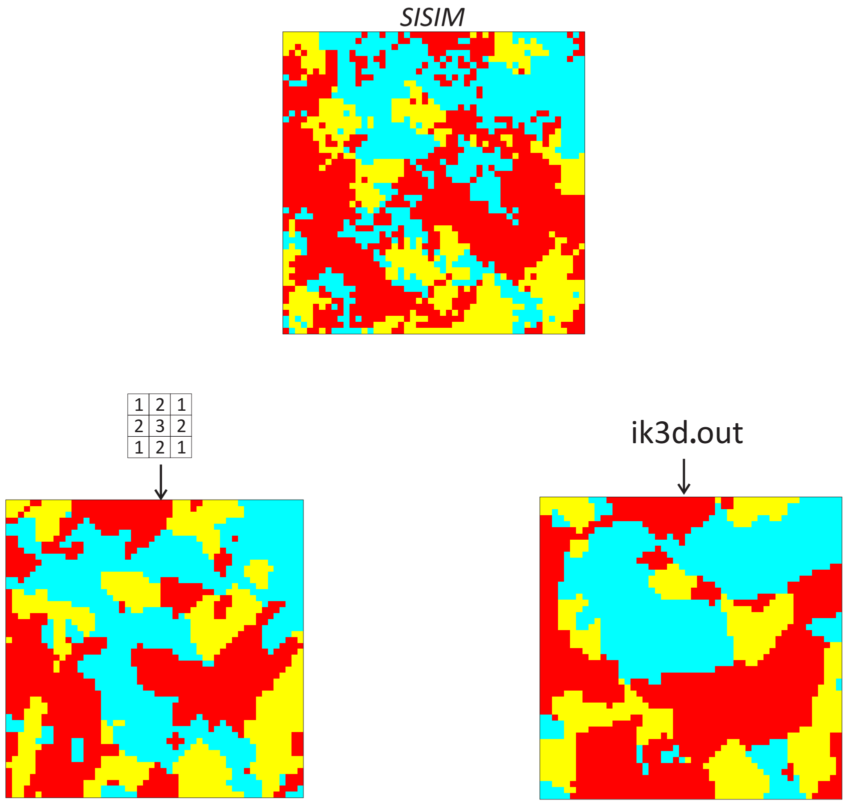

Figure 3: An original sequential indicator simulation is shown (upper). Cleaned images using user-input weights (bottom left) and using indicator kriging (bottom right) are shown.

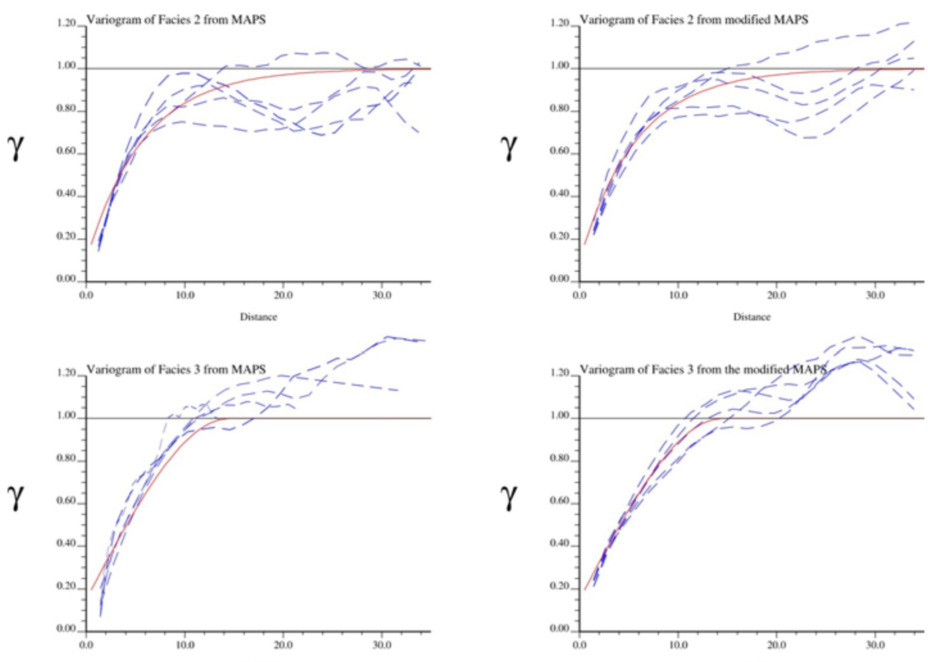

Figure 4: Variogram checking for isotropic user input cleaning weights and kriging based weights.

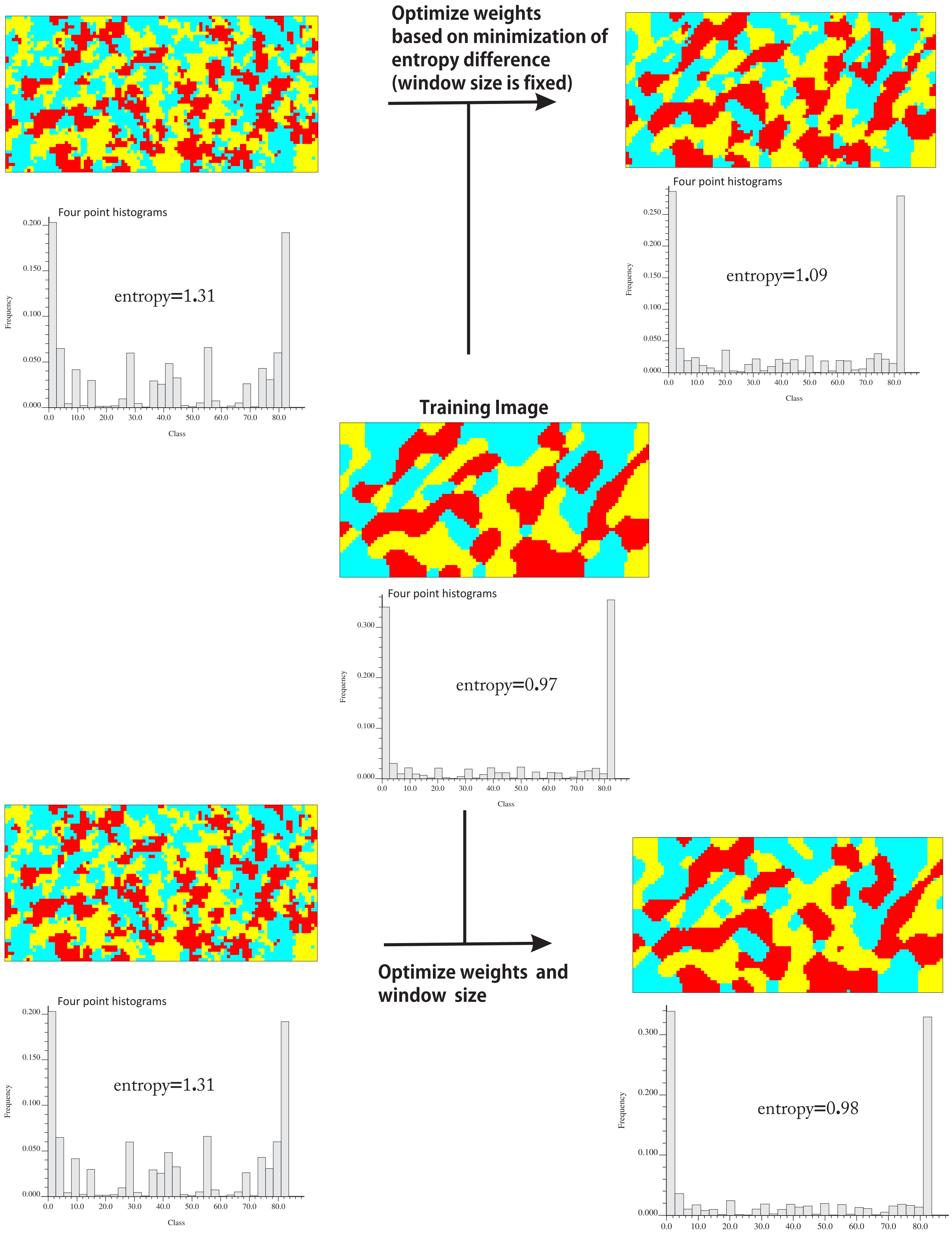

Figure 5: Multiple-point histogram based cleaning results.