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Clustering of Geological Models for Reservoir Simulation

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Summary

Geological uncertainty affects the forecast of reservoir performance. To quantify such uncertainty, geostatistical methods are used to generate multiple equiprobable realizations. A large set of geological realizations can represent the associated spatial uncertainty. As flow simulation over a large set of geological models is very costly, especially for complex processes such as SAGD, it is important to select a subset of geological realizations that reasonably represent the overall uncertainty. The methods to select representative realizations are based on dynamic and/or static data. The methods based on dynamic data are computationally costly as they need flow simulation. The methods based on static data are preferable if they can provide reasonable results. The approaches like probability-based technique (Li & Floudas, 2014) or ranking (Deutsch & Srinivasan, 1996) suffer from computational cost or unscaled geological properties.

In this work, a clustering technique based on static data is used to select a few representative models from a set of geological realizations. The Jensen-Shannon (JS) divergence (Cover & Thomas, 1991; Endres & Schindelin, 2003) is used as the dissimilarity distance to calculate the dissimilarity between any pair of realizations. Geological realizations consist of patterns that have complex structures. These structures may not be detectable and classifiable by simple linear techniques. Hence, Kernel k-means algorithm is used to identify nonlinear structures inherent in the data. Multidimensional scaling (MDS) is used to project the realizations into 2D space. This visualization can be used as supporting visual evidence to show the relative distance of realizations.

Workflow

Multiple-point statistics (MPS) methods rely on a training image (Khani et al., 2017, 2018a, 2018b). Training image is a non-conditional and purely conceptional depiction of a reservoir model and can be considered as a set of patterns. First, a training image is scanned using a template (i.e., a multiple-point configuration) and a pattern database is constructed. Then patterns are grouped into clusters using the kernel k-means clustering method. The mean of patterns within each cluster or a medoid pattern can be used to calculate the prototype for each cluster. Thus, a cluster-based histogram is made, in which each bin represents a prototype, and the vertical axis corresponds to the number of patterns in each cluster. Then, an MPS method is employed to generate a set of realizations using the training image. The pattern data base for each generated realization is constructed by scanning the realization using the template. Next the Euclidean distance between each pattern of realization and the training image prototypes is calculated, and the pattern is assigned to the closest prototype. Therefore, realizations and the training image histograms have the same bins and are comparable. Here, the training image is considered as a reference. If there is no training image and only a set of realizations is available, one of the realizations can be considered as the reference as all of them are equiprobable. For illustration purposes, Figure 1 shows a training image, its 41 prototypes, cluster-based histograms of 300 realizations and the cluster centers.

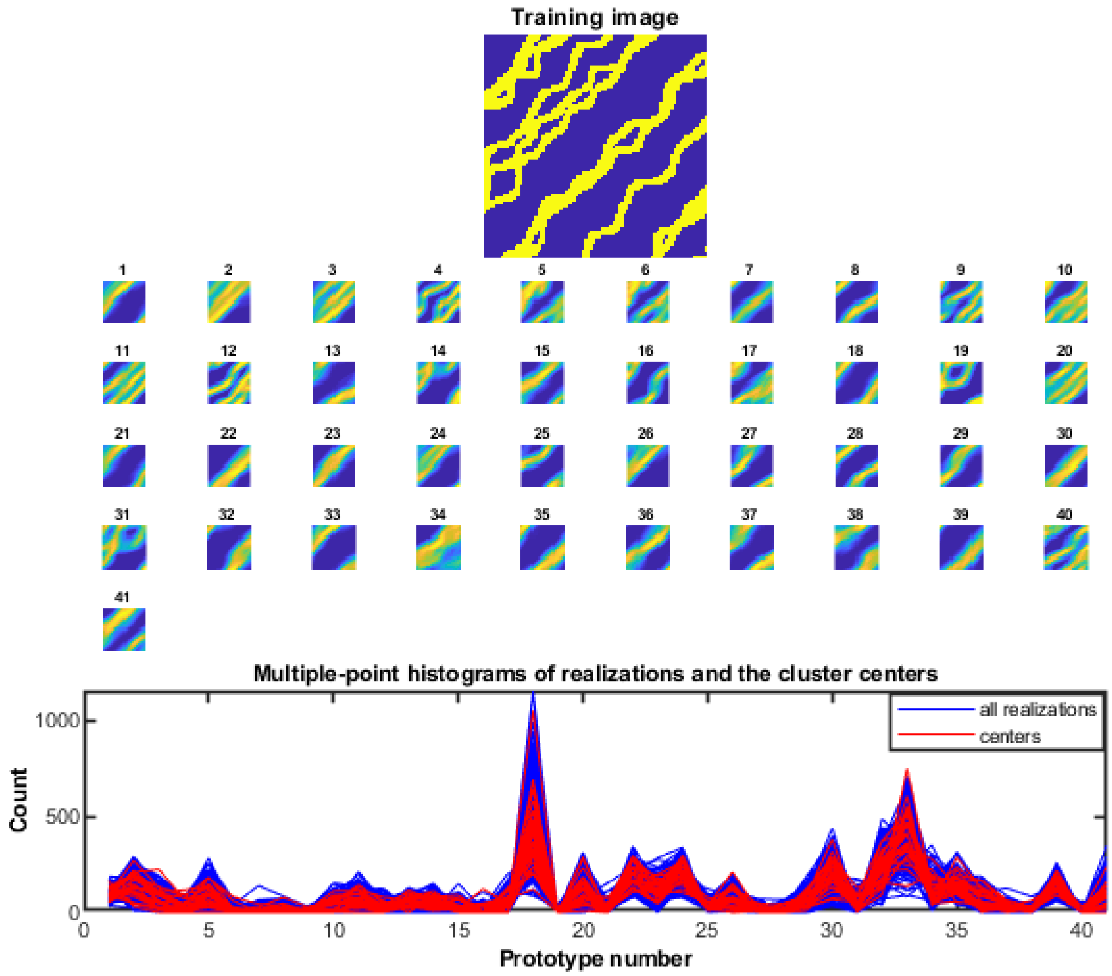

Figure 1: A training image, prototypes, cluster-based histograms of realizations and the cluster centers.

After calculating the cluster-based histograms, Jensen-Shannon (JS) divergence is used to calculate similarity between two probability distributions. The JS divergence is a symmetrized and smoothed version of the most important divergence measure of information theory, the Kullback-Leibler (KL) divergence. The KL divergence for two probability distribution P and Q is defined as follows:

$$D_{KL}(P\|Q) = \sum_{x \in \chi} P(x) log \frac{P(x)}{Q(x)} \quad (1)$$

where χ is the same probability space. The JS divergence is defined as follows:

$$D_{JS}(P\|Q) = \frac{1}{2}D_{KL}(P\|M) + \frac{1}{2}D_{KL}(Q\|M) \quad (2)$$

where $M = \frac{1}{2}(P + Q)$

The kernel function in this study is the Gaussian radial basis function.

Results

Figure 2 visualizes the resulting permeability-based clusters by the projection of realizations into 2D space using MDS. Each point corresponds to a realization. The cloud of points shows the space of uncertainty. Figure 3 presents the eigenvalues and the cumulative percentage of contribution of eigenvalues to the total sum of all eigenvalues. A large contribution of the first two eigenvalues means that the higher dimensions have a small percentage of the total distance.

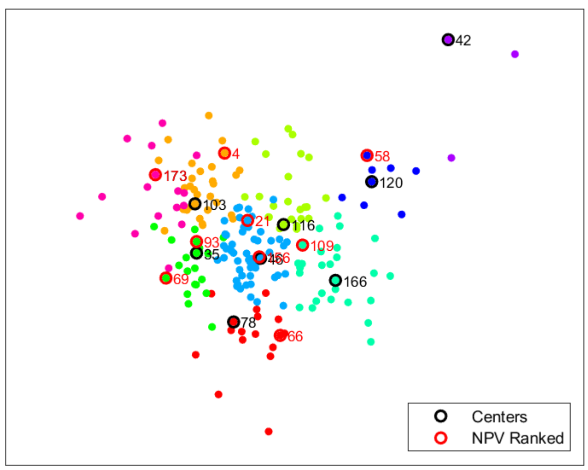

Figure 2: Projection of realizations into 2D space using multidimensional scaling (MDS). Points with the same color belong to the same cluster. The black circle shows the representative of each cluster.

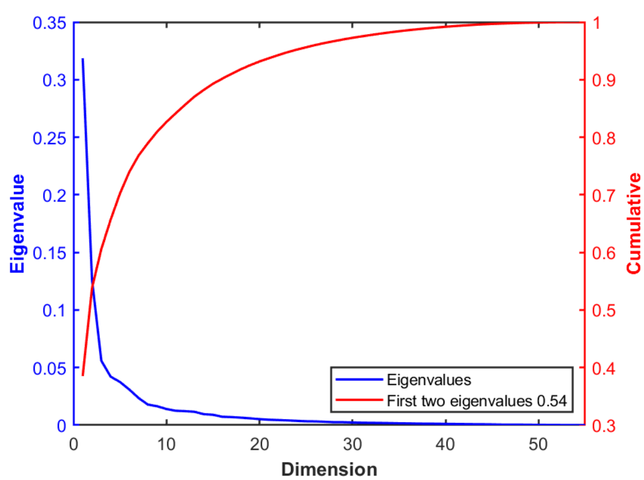

Figure 3: Scree plot of eigenvalues

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