Seismic zonation performance measures

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ABSTRACT

Seismic cluster analysis is used to create seismic zones for use in flow simulators. Several analyst decisions are required during the cluster analysis and subsequent regionalization procedures. These decisions lead to different cluster groupings and seismic zones. The quality of the clusters is measured by the isolation ration. The isolation ration indicates how well defined and different clusters are from other clusters. The homogeneity of the final zones is a measure of the quality of the final seismic zones. Resolution is best achieved by avoiding very large zones that cross broad areas of the domain. The number of clusters, the choice of weighting matrices and the number of small zones to remove must be chosen to balance homogeneity of the seismic zones with resolution.

INTRODUCTION

In Bentley et al. (2000a), we introduced a seismic cluster analysis method to delineate contiguous zones of similar seismic response. The purpose was to reduce the number of parameter zones in flow simulation models. The fundamental assumption is that spatially continuous areas of similar geophysical response are areas of relatively homogeneous hydraulic properties. Flow parameter zones were created for use in an automated history-matching algorithm (Bentley et al., 2001b). The algorithm updated the porosity and permeability of the seismic zones created for a reservoir simulator by jointly matching production history and time-lapse seismic data. Although the seismic zones appeared to work as well as the unconstrained full dimensionality model, measures for the quality of the seismic zones were lacking. This paper introduces and discusses quality measures for the seismic zoning.

THEORETICAL OVERVIEW

It is assumed that a geologic interpretation has defined the geometry of the aquifer boundaries and significant, well-defined lithologic units. A geologic mapping is then conducted within these boundaries. The process of geologic mapping, or, in the present case, zone definition, involves the identification of homogeneous regions (Harf & Davis 1990). The first step is typification or classification, in which the distribution of multivariate attributes is divided into a set of classes. The second step consists of regionalization, in which classes from the first step are divided into continuous regions of relatively homogeneous classes. Cluster analysis is used to classify points within a seismic volume into categories of similar seismic response. Clustering is done on the basis of seismic attributes. After spatial filtering, spatially continuous areas containing elements with the same classification category are grouped into seismic zones. The processing steps are (Bentley et al., 2000a,b),

1. Remove grid points that contain outliers in any seismic attribute.

2. Scale each attribute to zero mean and unit variance.

3. Use principal component analysis to transform the scaled attributes to uncorrelated principal component attributes.

4. Principal component attributes are grouped into categories of similar seismic response using cluster analysis.

5. Upscale the seismic grid to the computational grid scale using a weighted voting procedure (morphing). This step is performed only if required.

6. Spatially filter cluster assignments to remove small, isolated spots using a weighted voting scheme.

7. Assign a seismic zone to spatially connected elements with the same cluster category.

Several analyst decisions in the cluster analysis procedure affect the number and the distribution of the final regions. Consequently, analysts need measures of the quality of clustering and the final seismic regions.

ANALYST DECISIONS

Our dissimilarity measure is,

$$d_{lk} = \sum_{j=1}^{N_P} W_j \left(a_{jl}^P - a_{jk}^P \right)^2 \tag{1}$$

where d_{lk} is the dissimilarity between the l^{th} and k^{th} objects (transformed attribute vectors associated with a location in the seismic data volume), N_P is the number of retained principal components and a_{jl}^P is the j^{th} principal component element of the l^{th} object. Superscript P is to indicate principal component data as opposed to the original data. The analyst must choose a weighting scheme. We have investigated two schemes, uniform weights and eigenvalue weights. For uniform weights, $W_j=1$. For eigenvalue weights, W_j is equal to the eigenvalue of that principal component. The eigenvalue weights put more weight on the principal components that have the most variance and reduce the weight on the principal components that have little variance.

The clustering algorithm that has been implemented requires the specification of the number of clusters. Consequently, the analyst must decide on the optimum number of clusters. Too few clusters will not resolve some of the differences in the attribute categories. Too many clusters will create heterogeneous zones when none are warranted.

Very small seismic zones of one or two elements have little influence on the flow system and cannot be resolved with a parameter estimation algorithm. Consequently, the analyst must decide on the size of isolated regions to remove. “Spot removal” removes isolated groups of cluster categories that would create zones smaller than a specified size. The cluster category of the isolated clusters are reassigned to the category of a neighbouring cluster group based on a weighted voting scheme. The isolated elements are reassigned cluster category until the dimensionality of the system becomes manageable. The analyst must decide on the voting weights and the ultimate dimensionality. In the examples that follow, we have attempted to limit the maximum number of zones to less than 100.

QUALITY MEASURES

The following are desirable attributes for clusters and the final regionalization.

1. The clusters should be as well separated as possible by the dissimilarity measure. The primary measure of the quality of clusters is the isolation ratio. The isolation ratio is calculated for each cluster category. It is defined as the maximum dissimilarity of any member within a cluster to the cluster centroid, divided by the dissimilarity of the cluster centroid to the centroid of the nearest (most similar) cluster. A small isolation ratio means that the spread within the cluster is small compared to the separation distance to the nearest cluster neighbour.

2. The final seismic zones should contain as homogeneous a set as possible of cluster categories. In other words, each seismic zone should contain mainly one cluster type. The homogeneity of clusters is analyzed by looking at the percentage of elements that are the majority cluster type of each region. Ninety percent means that one out of ten elements in a seismic zone was reassigned from another cluster category. These results are presented as histograms and maps.

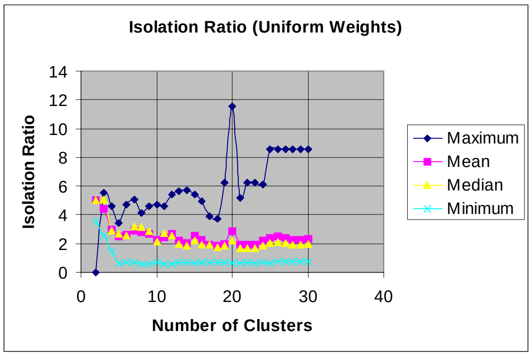
3. The final seismic zones should be small enough to capture the heterogeneity of the seismic attributes and assumed hydraulic property distribution. Extremely large zones that cross large regions of the domain are undesirable. Visual inspection of the final regional maps and monitoring the number of elements in the largest zones are the main tools for assessing the resolution of the seismic zones.

EXAMPLE

Data from a three-dimensional seismic survey in the Gulf of Mexico will be used to demonstrate the method. The survey was conducted over a turbidite sheet sand reservoir offshore Louisiana before production (Huang et al. 1997, 1998). The data from the top of the target zone was extracted and used to perform a 2-D seismic zonation for eventual use in a flow model. There are 15,306 seismic elements in the two-dimensional grid that covers the survey area. From the many possible seismic attributes, seven were chosen for use in the seismic zonation procedure. Clusters were created using instantaneous phase, instantaneous amplitude, instantaneous frequency, amplitude-weighted frequency, energy-weighted instantaneous frequency, average energy and arithmetic mean. These attributes were chosen because previous work indicated that they were the most sensitive to changes in porosity. Bentley et al. (2000b) describe the clustering algorithm and history matching results.

Isolation Ratio

Clustering was conducted on the principal component-transformed attributes. Clusters were computed using uniform weights and eigenvalue weights. Clusters were constructed for two to thirty clusters. The maximum, mean, median and minimum isolation ratio for the clusters are shown in Figure 1. The isolation ratio declines rapidly until about 5 clusters, then levels off with some fluctuations. The eigenvalue clustering has a lower isolation ratio than the uniform weight clustering. The mean and median isolation ratios of the eigenvalue weighted clusters are slightly less than the uniform weights isolation ratios and the maximum isolation ratios values are generally much less than those of the uniform weight clusters. Consequently, we chose to continue the comparisons with the eigenvalue-weighted clusters.



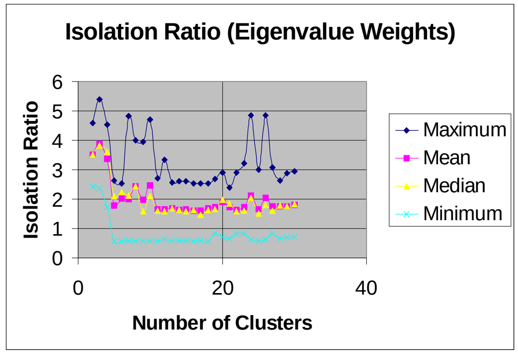


FIG. 1. Isolation ratios versus the number of clusters for uniform weights and eigenvalue-weight derived clusters.

Regionalization and spot removal

The results of three regionalizations are presented for illustration. Clusters of six, seven and eleven categories were created using eigenvalue weights. The isolation ratios for these three groupings are similar (Figure 1), and by this measure they are approximately the same quality. The three clusterings were upscaled using a three-by-three voting template with uniform weights, centred on the nine cells to be upscaled. This resulted in an upscale domain of 1716 active elements.

Prior to spot removal, the number of upscaled seismic zones were 228, 259 and 495 for the six, seven and eleven cluster category images. The greater the number of cluster categories, the more seismic zones that are expected.

The six category cluster had spots of one removed using a voting template with weights of one for the face-connected elements and 0.7 on the diagonal-connected elements (Figure 2). The seismic zones are shown in Figure 3. The image contains 109 seismic zones. Six percent of the elements were changed to different cluster categories during the spot removal and the comparison with the original upscaled image is shown in Figure 4. The homogeneity of the seismic zones is shown in Figure 5.

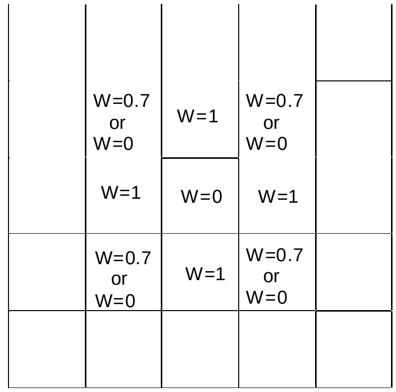


FIG. 2. Voting templates for spot removal.

The seismic zones for this case are uniform and only 6% of the element categories have been changed. The three largest zones contain 493, 257 and 110 elements. The largest zone (Figure 3) stretches across broad regions of the domain. Consequently, this zonation will perform poorly for flow zones. Several corner connections cause large blocks of elements to be grouped together. The problems with this seismic zonation are caused by too few cluster categories and weighting the corner connection nodes.

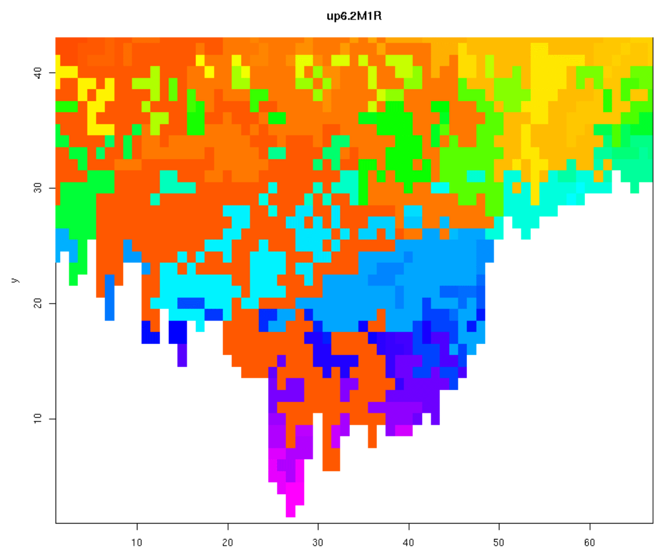


FIG. 3. Seismic regions from 6 cluster with spot removal of zones one.

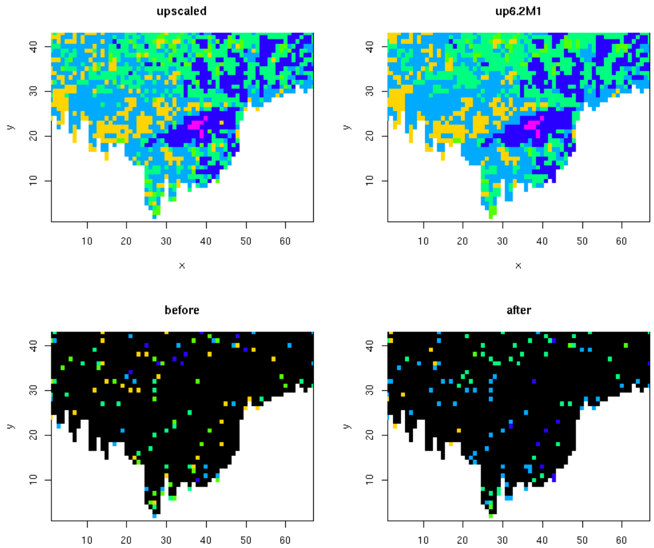


FIG. 4. Difference between original 6 cluster element categories and 6 cluster element categories after spot removal of zones of 1.

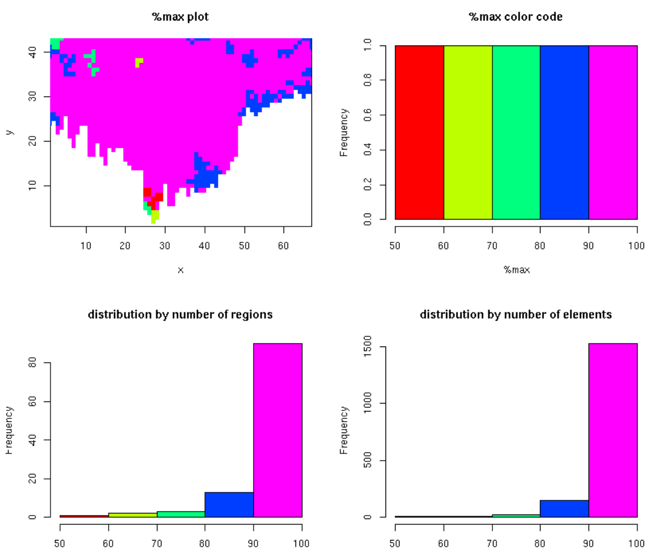


FIG. 5. Percentage of seismic zones occupied by the majority cluster category for six cluster categories and spot removal of one.

The seven cluster category image had spots of two or less removed using the weighting template with *W=0* for the corner connected elements (Figure 2). This biases the reassignments towards elements connected along faces as opposed to corners and should reduce the number of corner connections. The seismic categories are shown in Figure 6, the difference between the original and the spot removal image in Figure 7 and the homogeneity of zones in Figure 8. In this case we are left with 78 regions. The three largest zones contain 260, 210 and 151 elements. 12 % of the elements have been reassigned cluster categories during the spot removal. Figure 7 shows that most of the zones have 80 to 100% of their elements retaining their original cluster categories. The homogeneity of the seismic zones is good, but not as good as the six cluster case with weighted corner connection template.

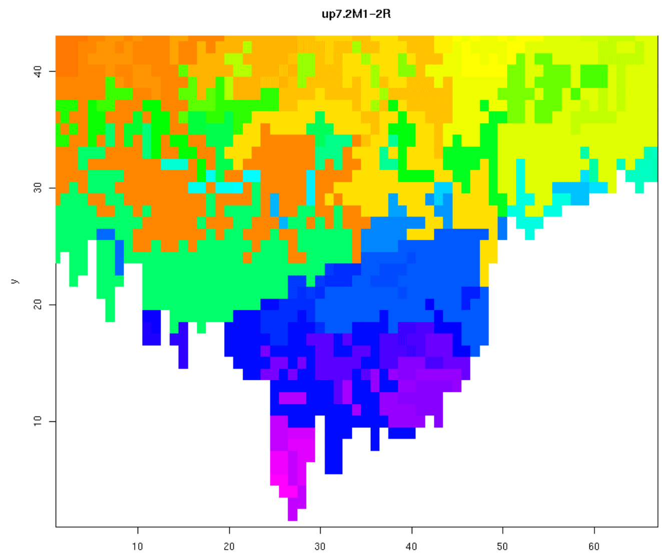


FIG. 6 Seismic zones for 7 cluster case with spots 2 or less removed.

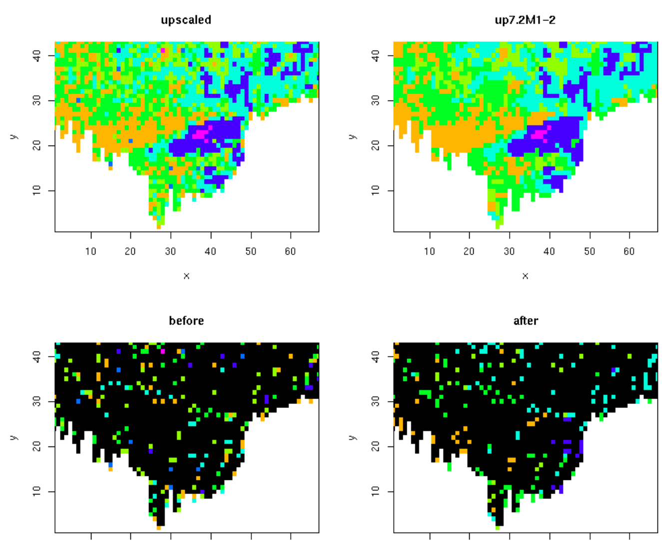


FIG. 7. Difference between original 7 cluster element categories and the 7 cluster element categories after spot removal of 2 and less.

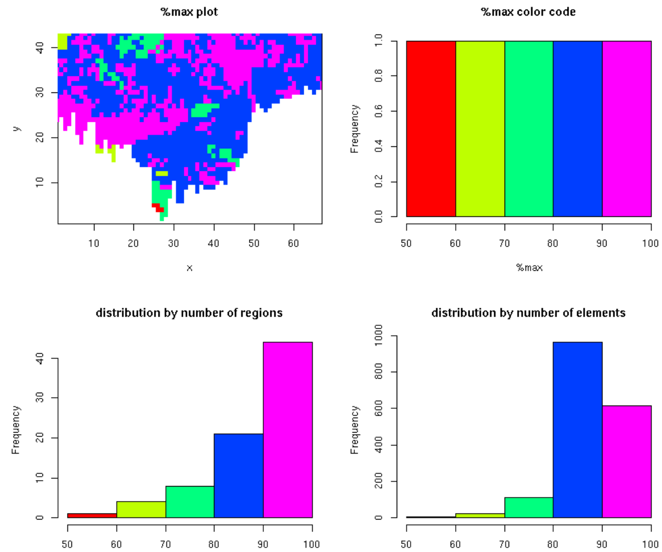


FIG. 8. Percentage of the majority cluster category in 7 cluster seismic zones after spot removal of zones 2 or smaller.

The eleven-cluster image had spots of two or less removed using the voting template with *W=0* on the corner elements. The seismic zones are shown in Figure 9, the difference of cluster categories before and after spot removal are shown in Figure 10 and the homogeneity of the clusters is shown in Figure 11. The image contains 103 regions, with the three largest regions containing 211, 170 and 123 elements. Twenty-five percent of the elements changed categories during spot removal. As can be seen in Figure 11, the majority of seismic zones only contain 70 to 80% of elements that retained their original cluster category. By introducing too many cluster categories, the homogeneity of the final seismic zones has been degraded.

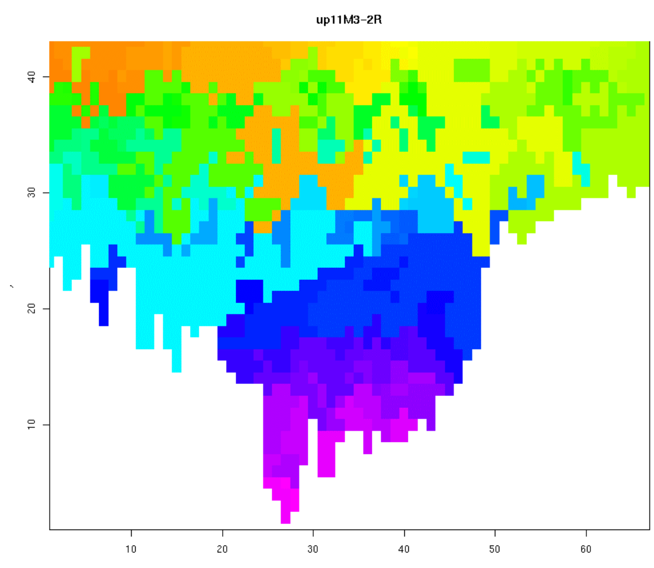


FIG. 9. Seismic zones from 11 clusters with spot removal of zones 2 and smaller.

The three examples show the tradeoffs inherent in seismic zoning. Too few clusters leads to good homogeneity, but the resolution is poor because of large zones that cover broad areas of the image. Too many categories leads to good resolution, but the quality of the seismic zones is poor because they are made up of too many elements that originally did not belong to the majority category. The seven cluster category with zones of two or less elements removed using voting weights that discriminate against corner connections seems to have the best tradeoff between resolution and homogeneity.

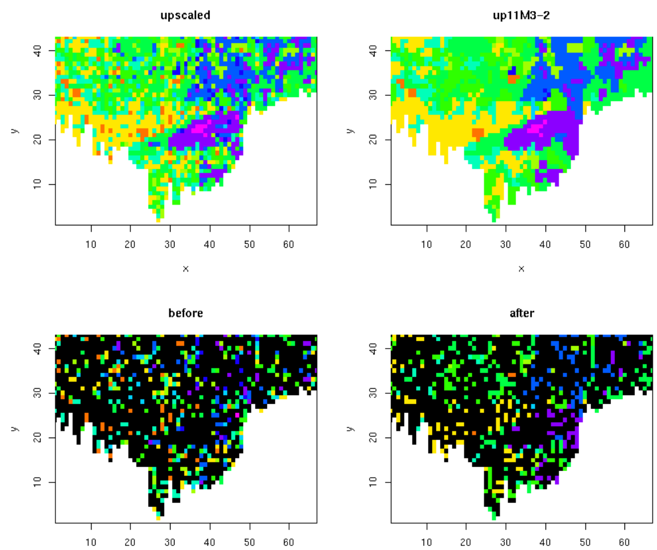


FIG. 10. Difference between the original 11 cluster categories and 11 categories after spot removal of two or less.

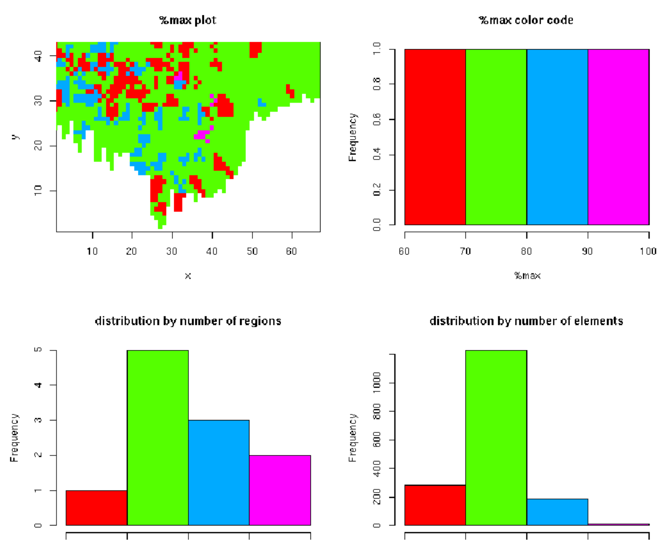


FIG. 11. Percentage of cells of the majority cluster in each zone for 11 clusters and spot removal of zones of two or less elements.

CONCLUSION

A method has been presented for creating parameter zones from a multi-attribute geophysical data set (Bentley et al., 2000a,b). The objective is to create zones that will reduce the dimensionality of decision variable sets used in fluid-flow simulator calibration routines. Several decisions are required of the analyst during cluster analysis and subsequent spatial filtering (spot removal). These decisions can lead to different seismic zones. We present several quality control measures for evaluating the quality of the final seismic zones.

The measures of quality are:

1. The isolation ratio is the main measure for the quality of the clustering
2. Homogeneity of zones is a measure of the quality of seismic zones.
3. Sufficient resolution as measured by the spatial distribution of the zones and the number of elements in the largest seismic zones.

In general, resolution and homogeneity are conflicting objectives so cluster number, voting weight templates and the size of spot removal must be adjusted until a reasonable compromise between homogeneity and resolution is achieved.

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