A Measure of Local Coherency Calculated from Wells for Data Checking and Geological Zonation

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A measure of coherency in facies between nearby wells is developed to aid in the processes of quality control of well data and geological zonation. Coherency measures the agreement between a well and its immediate neighbors based on structural markers and facies interpretations. The calculation can be done incrementally on sets of wells to identify incoherencies caused by errors in interpretation, measurement differences, data acquisition problems or actual changes caused by geological differences. Attributes may include the year a well was interpreted or included in a database, the interpreter, or what logging tool was used. Coherency is also used as a similarity metric in a hierarchical clustering algorithm for geological zonation. Results are applied in several examples that demonstrate the use of coherency and clustering to quality control and clustering data into geologically similar objects.

1. Introduction

Quality control of well data can be a time-consuming process in reservoir characterization and geomodeling studies (Theys, 1999; Deutsch, 2002). Data may be collected over many years prior to production. During this time, technologies for data acquisition change and multiple geologists and well log analysts handle the data, undoubtedly with some variation in the subjective process of interpretation. Two particular types of data that are prone to inconsistencies are structural markers and lithology indicators / facies due to the potentially subjective nature of these data types (Hein et al, 2002). When variations, inconsistencies or incoherencies can be detected during a quality control study, the database may require attention to improve the resulting geological models and engineering studies.

Variations in a database may be subtle and go unrecognized, especially when the database contains hundreds of wells and spans more than a decade of data acquisition. Such a scenario is typical of large oilsands mining projects, mature fields heading into enhanced recovery stages of production and of in-situ production of heavy oil. Subtle incoherencies may be perceived as inconsequential; however, they may have a significant impact on parameters for geomodeling, such as the variogram and local accuracy of prediction. In this work, a measure of coherency is defined to help detect wells that are inconsistent within a database. Coherency is calculated between a well and its immediate neighbors based on several parameters including the spatial position of wells, the facies interpretations along the wells, and the similarity between facies. The calculation is fast and automatic making it possible to detect incoherency in very large databases.

Resulting coherency measures for each well depend on the space considered. There are often two spaces in geomodeling including physical space where the wells exist in present time and modeling space where the effects of time on the depositional environment have been accounted for. Modeling space may also be referred to as stratigraphic space or geo-chronologic space (Deutsch, 2002; Mallet, 2004). Variogram modeling and estimation using kriging is done in modeling space. The spatial correlation of properties is higher in modeling space; therefore, so is the coherency. Another use of the coherency measure is to assess the quality of the transformation from physical space to modeling space. No improvement in coherency should raise some concern. To help assess how good an improvement is made, the coherency can be maximized by adjusting the vertical position of wells in a database. In cases where maximization does not change the coherency, the modeling space is optimal in reference to the coherency measure. In cases where large changes in coherency are observed, it may be necessary to re-evaluate the transformation process from physical to modeling space. A large change may also indicate a well bust.

Incoherencies in a database are not necessarily due to variations in interpretation or differences in technology. Rather, they may be a product of the depositional environment. For example, a middle estuarine environment with sinuous channels, inclined heterolithic strata (IHS), breccias, and other complexities may appear highly incoherent due to the heterogeneity in facies (McPhee and Ranger, 1998). In this case, the measure of coherency has a secondary use, that is, to aid in the identification of geological zones based on the facies designations. Facies intervals along wells are clustered with nearby wells into geological objects, where the coherency is used as a similarity metric. Such geological zonation is important for delineating regions that are stationary for geostatistical modeling. The clustering process can also be utilized for quality control, detecting boundaries between different geological successions, and trend modeling.

2. Methodology

2.1. Coherency

The measure of coherency between two vertical or quasi-vertical wells was derived based on Equation 1 for the covariance function, where z is a random variable, $\mathbf{h}$ is a vector separating two points $\mathbf{u}_i$ and $\mathbf{u}_i + \mathbf{h}$, $N(\mathbf{h})$ is the number of pairs separated by $\mathbf{h}$, and μ_0 and $\mu_{\mathbf{h}}$ are the expected value of z defined by Equations 2 and 3.

$$C(\mathbf{h}) = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{u}_i) \cdot z(\mathbf{u}_i + \mathbf{h}) - \mu_0 \cdot \mu_{\mathbf{h}} \tag{1}$$

$$\mu_0 = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{u}_i) \tag{2}$$

$$\mu_{\mathbf{h}} = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{u}_i + \mathbf{h}) \tag{3}$$

The covariance function measures how two sets of data separated by $\mathbf{h}$ relate, or how coherent they are. Considering z as a Gaussian random variable with unit variance, a covariance of zero indicates no coherency whereas a covariance of 1 indicates full coherency. The covariance between two vertical wells, denoted well A and well B, separated by $\mathbf{h}$ in an aerial plane is evaluated with Equation 1 by considering all $\mathbf{u}_i$ along well A and all $\mathbf{u}_i + \mathbf{h}$ along well B. If the two wells are at the same depth, sample the same depth interval, and $z(\mathbf{u}_i) = z(\mathbf{u}_i + \mathbf{h}) \forall i$, the covariance or coherency is 1. However, not all pairs between the wells have the same $\mathbf{h}$ when the depth coordinate is considered because only those pairs that exist in the same aerial plane are separated by $\mathbf{h}$.

The covariance measure in Equation 1 does not allow for any flexibility due to differences in depth between two wells and $\mathbf{h}$ must be permitted to vary within some limits. A search window is introduced to allow some variation in $\mathbf{h}$ to account for minor stratigraphic variation between pairs of wells (Figure 1). Search parameters include a search angle, θ, and maximum search radius, r. For each point $\mathbf{u}_i$ along well A, a set $\mathbf{u}_j \in S_i$ along well B are found within the search constraints such that $\mathbf{u}_j - \mathbf{u}_i \geq \mathbf{h}, \forall \mathbf{u}_j \in S_i$. Even though some variation in depth is accounted for this way, pairs that exceed $\mathbf{h}$ are penalized. For wells A and B that have identical z values, the coherency should be zero if their depths differ by an amount greater than r so that problems related to well busts or transformations from physical to stratigraphic space can be identified. A weight function defined by Equation 4 is introduced, where α_{ij} is the dip angle between $\mathbf{u}_i$ and $\mathbf{u}_j$ and π/θ is a scaling factor so that $\lambda = 0$ when $\alpha = \theta$.

$$\lambda\left(\mathbf{u}_i, \mathbf{u}_j\right) = \cos\left(\pi \alpha_{ij} / \theta\right) \tag{4}$$

Because the search parameters yield a set of points along well B for each point along well A, only the pair with maximum weighted coherency is retained. Otherwise, the weight function could lead to a reduced (averaged down) coherency measure when actual coherent intervals between the wells are smaller than the search radius. The final equation for coherency between wells A and B is given by equation 5, where N is the number of samples along wells A and B and $\mathbf{u}$'s have been dropped for clarity.

$$C\left(A, B\right) = \frac{1}{N} \sum_{i=1}^{N_A} \max_{\forall j \in S_i} \left\{ \lambda_{ij} M(z_i, z_j) \right\} + \frac{1}{N} \sum_{j=1}^{N_B} \max_{\forall i \in S_j} \left\{ \lambda_{ji} M(z_j, z_i) \right\} \tag{5}$$

Equation 5 involves the computation from well A to well B and B to A so that the coherency function is symmetric. Unlike the covariance equation where $z(\mathbf{u}_i) z(\mathbf{u}_j = \mathbf{u}_i + \mathbf{h}) = z(\mathbf{u}_j) z(\mathbf{u}_j - \mathbf{h})$, the max function is non-symmetric, that is, $\max\left(z_i z_j\right) \forall j \in S_i = \max\left(z_j z_i\right) \forall i \in S_j$ does not necessarily hold. The parameter, $M(z_i, z_j)$, is a similarity metric that replaces the product, $z(\mathbf{u}_i) z(\mathbf{u}_i + \mathbf{h})$ in Equation 1 and measures the similarity between two values. For continuous variables, M is defined by Equation 6, where z should be transformed to the [0,1] interval so that the coherency measure ranges from 0 to 1. Alternatively, the covariance function of the random variable z could be used.

$$M(z_i, z_j) = 1 - \left(z_i - z_j\right)^2, z \in [0,1] \tag{6}$$

For categorical variables, M is a symmetric user-defined matrix with entries that define the similarity between different categories and ranges from 0 to 1. For example, if M is an identity matrix, categories are completely dissimilar. Categories that are somewhat similar can be given a similarity value greater than zero. This may be the case for multiple facies that are found in the same geological feature such as a point bar, or for multiple rock types with considerable overlap between the underlying rock property distributions. An example of a similarity matrix from an estuarine depositional environment with 5 facies is provided in Table 1. Breccia and channel fill are assigned a similarity of 0.5 as breccia tends to deposit in the base of channels. Point bar sand and shale are also deposited in the same geological object.

Table 1: Example similarity matrix for an estuarine depositional environment.

Facies	Cross stratified sands	Breccia	Point bar sand	Point bar shale	Channel fill
Cross stratified sands	1	0	0	0	0
Breccia		1	0	0	0.5
Point bar sand			1	0.5	0
Point bar shale				1	0
Channel fill					1

Computing the coherency of a well, A, with n of its immediate neighbors, $B_k, k = 1, \dots, n$, is the average coherency between A and each B_k defined by Equation 7, where ω_k are weights that can be computed in a variety of ways such as equal or inverse distance.

$$C(A) = \frac{1}{\omega_k} \sum_{k=1}^{n} \omega_k C(A, B_k) \tag{7}$$

If all wells are approximately equally spaced, then equal weights may be used. When significant variation in well spacing exists, then wells further away should have less impact on the coherency calculation than nearby wells and a weighting scheme such as inverse distance is more appropriate.

Equation 7 provides a quantitative assessment of the agreement between a well and its local neighborhood. A high coherency indicates wells have a similar arrangement of facies or other reservoir properties. Low coherency may indicate a few different issues or characteristics of the data including: wells that have poor agreement between reservoir properties; wells that have a significant depth offset such as well busts; and reservoir properties that have a correlation length less than the well spacing. The last result is a characteristic of the data and would likely result in low coherency measures for all wells in a database.

2.2 Maximizing Coherency

Determining the maximum coherency is an optimization problem. A gradient descent algorithm is developed that changes the vertical position of wells until the average coherency of all wells is maximized. The gradient is approximated for each well pair by evaluating the coherency at two points: the coherency after shifting the well some distance, Δz, in the negative z direction and again in the positive z direction (Equation 8), where z is the vertical coordinate.

$$\frac{dC(A, B_k)}{dz} = \frac{1}{2\Delta z}\left[C_{+\Delta z}(A, B_k) - C_{-\Delta z}(A, B_k)\right], k = 1, \dots, n \tag{8}$$

Since shifting well A down is equivalent to shifting well B_k up, the relation 9 holds.

$$\frac{dC(A, B_k)}{dz} = -\frac{dC(B_k, A)}{dz} \tag{9}$$

The total gradient for well A is then computed using Equation 10, for all wells B_l that have A as an immediate neighbor.

$$\frac{dC(A)}{dz} = \sum_{k=1}^{n} \frac{dC(A, B_k)}{dz} - \sum_{l} \frac{dC(B_l, A)}{dz} \tag{10}$$

Vertical positions of wells are updated by taking a step in the gradient direction by Equation 11, where m is the iteration, z_i is the top of a well, α is the step size, and N is the number of wells.

$$z_i^m = z_i^{m-1} + \alpha \frac{dC_i^m}{dz}, i = 1, \ldots, N \tag{11}$$

A line search algorithm called the golden section search is used to determine the step size that maximizes the coherency for the given gradient. As wells are adjusted, the gradient changes since different facies intervals align at different angles. The algorithm is as follows:

I. Compute initial coherency.
II. While $\alpha > 0$ and $\|dC_i^m/dz\| > \varepsilon$
   1. Approximate the gradient using Equation 8 and 10.
   2. Find α to maximize the coherency using a line search.
   3. Update z using Equation 11.

Because the step size is computed to maximize the average coherency of all wells together, it does not guarantee that the coherency of each well will increase. This implementation of gradient descent is also not a global optimization algorithm, that is, it will likely converge to a local maximum. Assuming the data and transformation from physical to modeling space is primarily of good quality, a local maximum is likely close to the global maximum and optimized well positions will provide an equal amount of information about data quality and space.

The optimization procedure is intended to provide information about the data including quality of facies and of accuracy or correctness of well positions in the depth coordinate. It may be used to check the goodness of a transformation from physical space to modeling space. For example, a large increase in coherency for a well in modeling space may warrant updating the transformation as long as such a change is geologically realistic or correct. A large increase in coherency may also indicate a well bust or problematic formation marker elevation. Optimized well positions should not be used blindly to define the modeling space.

2.3 Coherency-based Clustering

The coherency measure defined by Equation 5 and 7 has other uses beyond identifying data quality issues. It can be used as a similarity metric for clustering data into geological objects or zones with similar properties. Developments made towards geological zonation involve categorical data, such as facies or rock type. For clustering, Equation 5 is used since it provides the similarity between two wells as opposed to a well with its surroundings as in Equation 7. The latter does not provide useful information to determine if wells belong to the same geological zone. A simple example with four wells and three facies demonstrates the concept of zonation and the different information provided from Equation 5 and 7 (Figure 2). Coherency between well pairs is used to detect where changes in zone occur; however, this poses problems when the coherency is greater than zero (Figure 2).

Coherency must be computed between smaller intervals along the wells to more accurately determine where geological zone boundaries exist. The smallest possible intervals to consider are individual sample points and the coherency is defined by Equation 8, where z_i and z_j are from different wells, A and B, that are immediate neighbors.

$$C\left(z_i, z_j\right) = \max_{\forall j \in S_i} \left\{ \lambda_{ij} M\left(z_i, z_j\right) \right\} \tag{12}$$

The number of pairs depends on the number of samples, N, and number of nearest neighbors, n, to consider and is equal to $R = N \cdot n$. Evaluating Equation 8 for all pairs yields a sparse symmetric $R \times R$ matrix, **C**. For small databases, this may not be an issue; however, the matrix can become substantial for databases with many wells having a small sampling interval. Developing the clustering algorithm in this fashion is an area of future study. To maintain a smaller matrix and accurately detect zone boundaries, wells are broken into intervals that have the same facies or rock types. In Figure 2, each well would be separated into three intervals and the number of coherency values increases from 3 to 9. Boundaries between well B and C in the upper and middle interval are detected since the coherency is zero and no boundary is assigned in the bottom interval since the coherency is 1.

In actual well databases, the zonation problem is three dimensional with much more variation in well elevations, geometry of nearest neighbor sets, facies, and geological architecture. This results in a variety of coherencies and adds complexity beyond that shown in Figure 2. A hierarchical clustering algorithm (Theodoridis and Koutroumbas, 2009) is used to process the sparse coherency matrix into a set of possible geological zones or objects and proceeds as follows:

I. Initialize set of clusters, $G_i, i = 1, \ldots, R$, that refer to facies intervals.
II. While $\max\{\mathbf{C}\} > u$
   1. Find i and j such that $C_{ij} = \max\{\mathbf{C}\}$
   2. Merge cluster G_j with cluster G_i, saving the result in G_i
   3. Update all entries in $C_{kl}, k = 1, \ldots, R, k \neq i$, where $l = i$ or $l = j$
   4. Zero all entries $C_{jl} > 0$ in $\mathbf{C}$.

In this algorithm, u is a coherency cutoff that defines when clustering is halted. Because $\mathbf{C}$ is sparse, setting $u = 0$ will not necessarily lead to one cluster as in typical hierarchical algorithms. The $\max\{\mathbf{C}\}$ operation finds the entry in $\mathbf{C}$ with maximum coherency. The merging operation in step 2 stores all items (facies intervals) contained in G_j within G_i. The update operation in step 3 finds all entries in $\mathbf{C}$ that have a positive coherency with the items in the new cluster G_i. If for a particular cluster k, both entries C_{ki} and C_{kj} exist, the coherency with G_i is computed using one of the linkage types for hierarchical clustering: average linkage that takes $(C_{ki} + C_{kj})/2$; single linkage that takes $\max\{C_{ki}, C_{kj}\}$; and complete linkage that takes $\min\{C_{ki}, C_{kj}\}$. Hierarchical clustering is often referred to using a dissimilarity measure where single linkage takes the minimum dissimilarity and complete linkage takes the maximum.

Several pieces of information are collected as clustering progresses including: the final cluster identifier; initial cluster identifier; and the coherency involved in merging an item with a cluster. Final cluster identifiers are assigned to every sample present in the database for visualization and further processing. Initial cluster identifiers are assigned to items in the order they are first merged together. As items are merged with existing clusters, they are assigned the initial cluster identifier of that cluster; however, when two clusters are merged, there is no change in the initial cluster identifier. This provides information about the growth patterns of the clustering process. Lastly, the coherency involved in tying an item to a cluster is recorded and can be used as a measure of the probability that that item belongs to the cluster.

4. Examples

The coherency measure, maximization, and clustering are demonstrated using a set of vertical wells that sample three different types of media: 1 – uniform random facies; 2 – an estuarine training image; 3 – a fluvial training image. The first data set is used as a control to observe coherency values that indicate poor data. Data sets 2 and 3 are used to assess the expected coherency of fluvial and estuarine deposition under ideal conditions. For maximization, the estuarine data set is used with a few wells shifted to simulate well busts or post-depositional deformation. Coherency clustering is applied to the fluvial data set.

Coherency

Data sets for demonstrating the coherency calculation are shown in Figure 3 with facies designations defined in Table 2 for the estuarine and fluvial examples. Facies for the random example are not associated with any particular geology. Data sets each consist of 256 wells that sample different grids with dimensions provided in Table 3. Coherency was computed using the three nearest neighbors to each well (Figure 4). Differences in the scale of geological variation between the estuarine and fluvial data are observed through the local variation in coherency, with more local variation for the estuarine data. Because there is no stratigraphic deviation among the wells, the search parameters were set to $\theta = 0.01$ degrees and $r = 1$ meters. Facies similarity matrices were set to identity matrices for the random and fluvial data. The estuarine data involved a facies similarity matrix with ones on the diagonal and a one between the point bar facies because they exist in the same geological object. Histograms of the resulting coherency indicate low coherencies with little variation for the random data, and moderate values with an average of 0.6 for estuarine and fluvial data (Figure 5). Coherency from the estuarine data had a variance substantially higher than the fluvial data. This is likely due to differences in channel wavelength, width, and sinuosity.

Table 2: Facies for estuarine and fluvial examples.

Estuarine Facies	Fluvial Facies
CSS – cross stratified sand	FP – flood plain
PBSH – point bar shale	CH – channel sand
PBS – point bar sand	LV – levee
BR – breccia	CS – crevasse splay
CH – channel fill	

Table 3: Grid sizes for example data sets.

Data Set	Nx, Ny	Nz	Dx, Dy	Dz
Random	200	100	25	0.1
Estuarine	140	80	25	0.25
Fluvial	256	128	16	0.16

To understand the meaning of resulting coherency, wells with low and high coherency are plotted with their three nearest neighbors for the estuarine data set (Figure 6). Conclusions are similar for the fluvial data set. For the low coherency well, it samples CSS from the upper channel succession and point bar from the lower succession. Nearby wells sample channel fill from the upper succession and CSS from the lower (wells 118 and 121), and point bar from the upper succession and channel from the lower in well 143. Because the wells are sampling different geological objects from the two successions, the coherency is low. For the high coherency case, all wells sample the same point bar object from the upper succession and CSS from the lower succession.

Low coherency results may be used to identify potential data quality issues. They encourage those involved with the data to visualize the data and determine the cause of the low result. In this case, the cause is due to the complex geology and is not a data quality issue. Results may be useful for determining the type of geology in the local neighborhood of the well. The interpretation of the coherency values is also important for coherency based clustering that is demonstrated later. Based on the coherency, it is possible to determine that well 336 does not belong with its neighbors and that well 204 could be clustered with its neighbors into a geological object.

Maximization

Coherency maximization is demonstrated using the estuarine data set with some of the wells shifted to simulate well busts or stratigraphic variation in well markers. In the case of stratigraphic variation, the purpose of the maximization procedure is to identify wells that may require adjustment to optimize the space for geostatistical modeling, that is, to improve the transformation from physical space to stratigraphic space. Twenty wells were selected with a variety of coherency values from the estuarine data. The z coordinates of the wells were shifted in the range (-4, 4) using uniform random numbers.

For the maximization procedure, the search angle was increased so that facies intervals along neighboring wells that will lead to a higher coherency are found. An angle of $\theta = 0.4$ degrees and search radius $r = 0.4$ meters were used. The number of nearest wells to use was also increased from three to five, which helps to smooth out the result. Results are shown in Figure 7. Wells were shifted close to their original positions, which are assessed by histograms of the initial shift, and the shift after optimization relative to the original well positions (Figure 8). Summary statistics are provided in Table 4. The three wells with an optimized relative shift greater than one meter are in a region with low coherent wells, much like well 136 from Figure 6. A consequence of the optimization procedure is that many wells are shifted to reach the maximum coherency, not only the 20 wells that were artificially shifted for the test. This information would normally not be available.

In cases where the wells are known to be accurately positioned in physical and stratigraphic space, the maximization procedure can be used to guide the gridding process. In this case, the grid conforms to the shift indicated by the maximization procedure and wells are not actually shifted.

Table 4: Shifted and optimized well position statistics.

Case	Mean	Standard Deviation	Minimum	Maximum
Shifted	0.05	0.74	-3.96	3.94
Optimized	0.05	0.24	-0.60	1.45

Clustering

Coherency based clustering is demonstrated using the fluvial data set. Clustering has several uses including the identification of stationary regions, detecting geological objects, detecting boundaries between different geological successions, building facies proportion trend models, and identifying questionable facies intervals. Work on post-processing the clustering results is still needed to evaluate these potential uses. This example applied the clustering algorithm and displays the resulting data that were clustered together in the same plan views and cross sections as Figure 3 for comparison. Data that belong to particular geological objects tend to be clustered together due to the high coherencies between the data. This does not provide any information as to the location of the boundaries between neighboring geological objects or their exact shape, which is an area of future work. For this example, indicator kriging is used to obtain an approximation to the location of geological object limits and shape that is easier to visualize than the sample data alone.

Clustering was run with the same parameters as maximization in the previous section: search angle and radius of $\theta = 0.4$ degrees and $r = 0.4$ meters and five nearest neighboring wells. This results in 363 clusters, 200 of which only contain one facies interval. For quality control purposes, these single item groups could be checked with surrounding data to make sure the facies are correct and that the assumptions regarding the depositional environment are correct. In cases where there is no explanation for the single item clusters, then such results are indicative of data with scales of heterogeneity smaller than the well spacing.

Visualization of the resulting clustering is done using closed polygons that indicate which data belong to the same cluster (Figure 9). Comparing this to the actual facies distribution, the match appears good considering no knowledge of the depositional environment was involved in the clustering. For the same reason, there are differences, for example, levee objects are not in the shape of levees. An area of future work to address this is to utilize training images to learn the tendency of geological objects to aid in the determination of object shapes and boundaries.

5. Conclusions and Future Work

This work introduced a measure of coherency that is useful for quality control and to aid in geological modeling, specifically for categorical variables. Quality control is an important stage of geo-modeling, but can be quite demanding for large databases. The coherency measure can be used to quickly identify potential problems with facies designations or well markers. Another use of coherency is clustering data into groups having similar facies. The approach is non-linear and resulting groups of facies can form objects with shapes that would otherwise be unattainable using traditional geostatistical approaches for categorical data.

Several areas of future work have been identified. The coherency measure has been developed for both continuous and categorical data. Testing with continuous variables is needed. It would also be beneficial to compute the coherency using a categorical variable and one or several continuous variables together. In this case, data with a high coherency will have similar statistical properties and coherency-based clustering would help to identify stationary regions. Another area of future research is to utilize the clustering and maximization procedures to aid in the process of geological gridding. More work is needed on the clustering algorithm including learning cluster shape and tendency from training images and post-processing clustering results into geological objects, facies trend models, and even facies realizations.

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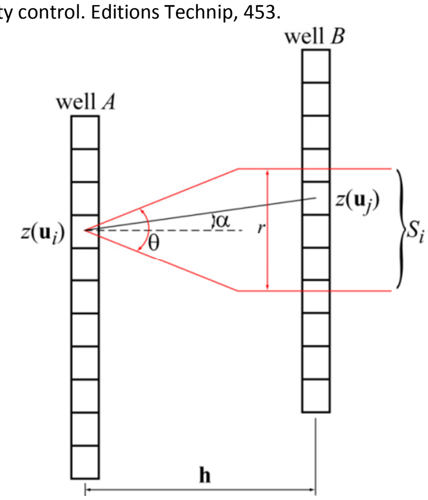

Figure 1: Parameters involved in the coherency calculation.

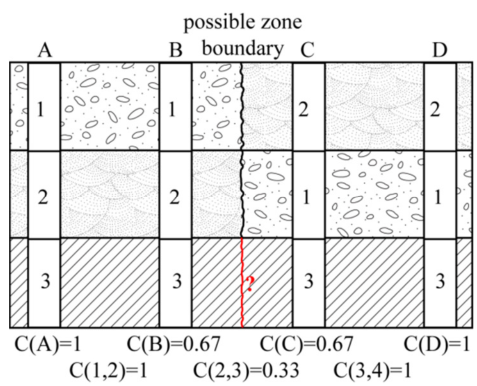

Figure 2: Basic concept of geological zonation using coherency. Wells are labeled A through D and facies 1 to 3. The difference between coherency of each well using the left and right neighbors and coherency between well pairs is shown. Determining if a zone boundary exists in facies 3 based on well pair coherency is problematic.

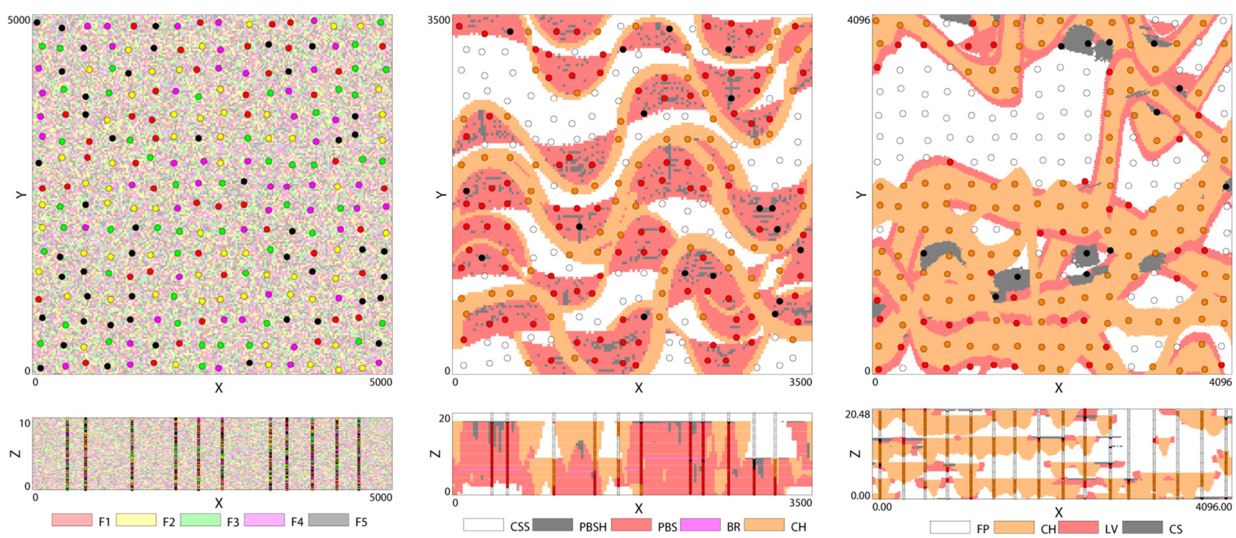

Figure 3: Example random (left) estuarine (middle) and fluvial (right) data sets for coherency. Cross sections are at approximately half distance along Y.

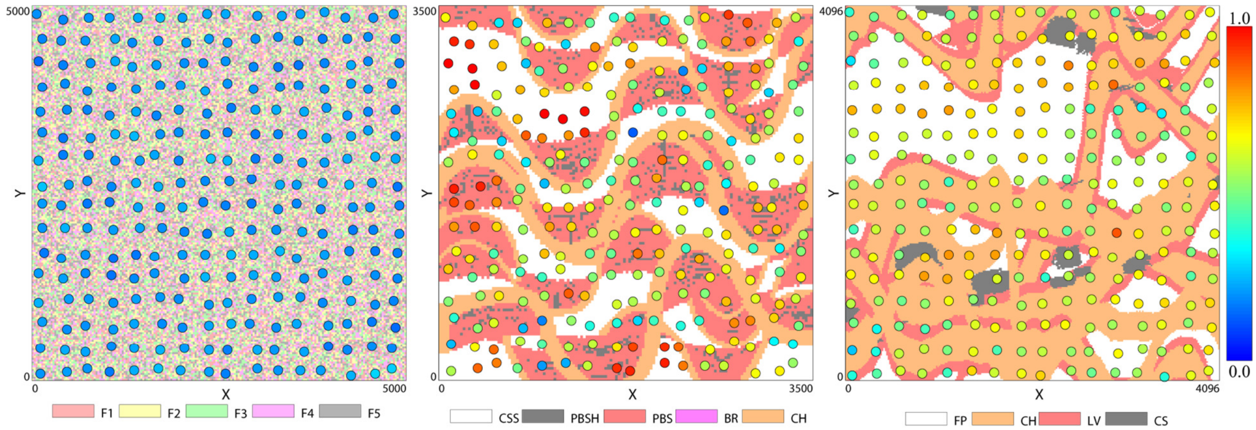

Figure 4: Coherency results for random (left), estuarine (middle) and fluvial (right) data sets.

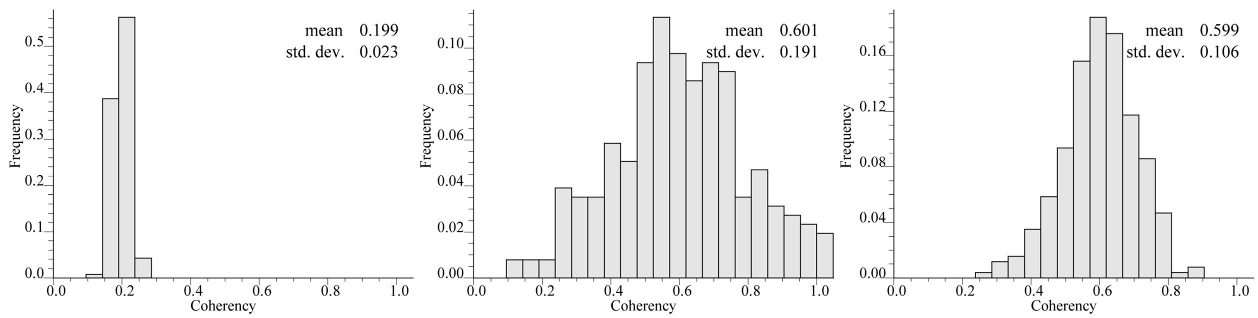

Figure 5: Histograms of coherency for random (left), estuarine (middle) and fluvial (right) data sets.

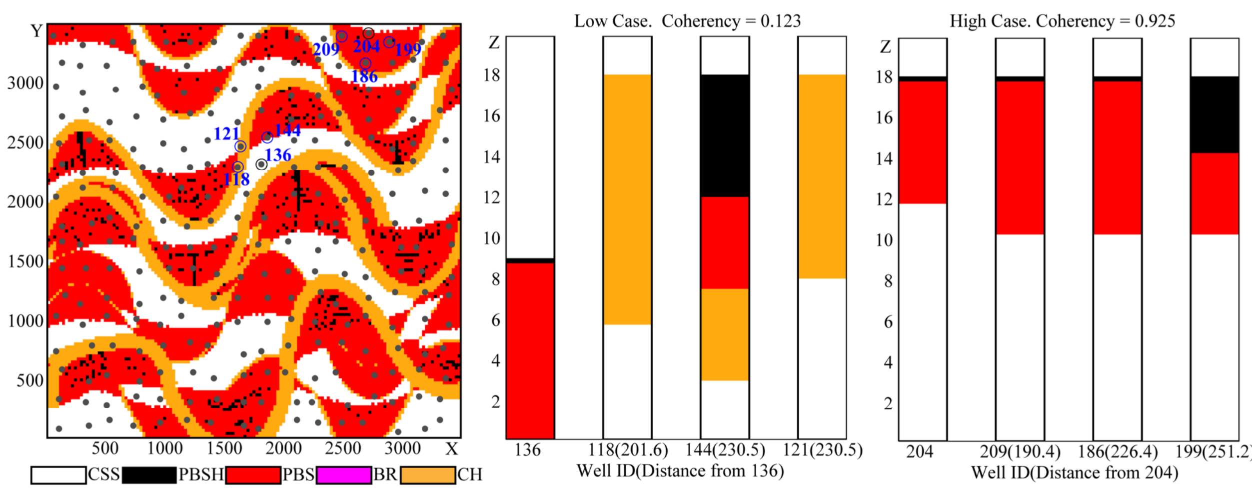

Figure 6: Examples of low and high coherency for the estuarine example. The slice at $z = 12.5$ of the estuarine model is shown in the location map.

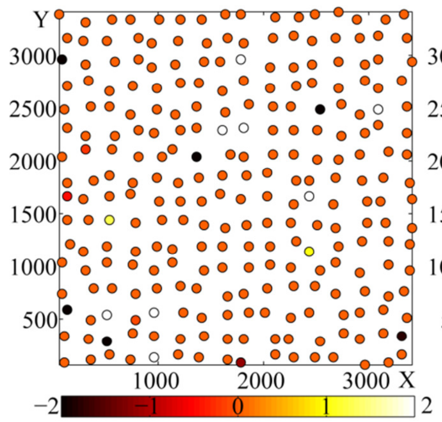

Figure 7: Example of coherency maximization showing initial shifted wells (left), the shift that leads to maximum coherency relative to the initial shift (middle) and relative to the original well positions (right).

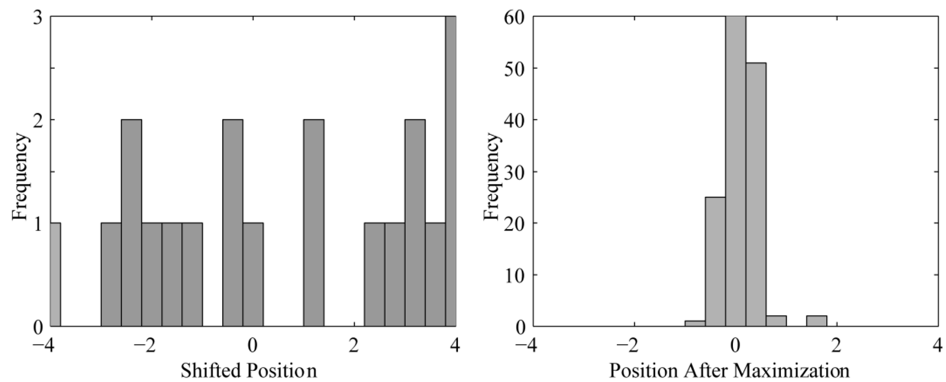

Figure 8: Histograms of shifted well positions (left) and well positions after optimization (right) relative to their original position.

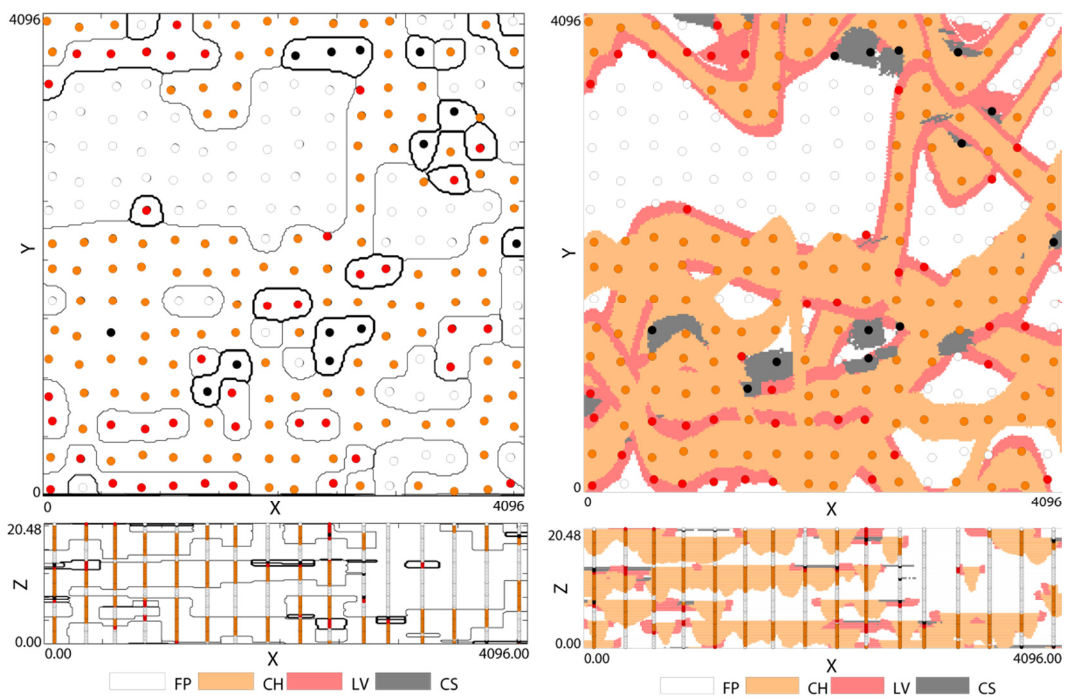

Figure 9: Clustering results summarized using polygons (left) compared to the actual facies distributions (right).