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Facies Modeling of Heterogeneous Carbonates Reservoirs by Multiple Point Geostatistics

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ABSTRACT

Facies modeling is an essential part of reservoir characterization. The connectivity of facies model is very critical for the dynamic modeling of reservoirs. Carbonate reservoirs are so heterogeneous that variogram-based methods like sequential indicator simulation are not very useful for facies modeling. In this paper, multiple point geostatistics (MPS) is used for facies modeling in one of the oil fields in the southwest of Iran. MPS uses spatial correlation of multiple points at the same time to characterize the relationships between the facies. A small part of the oil field, in the vicinity of the simulation grid, is used as a training image, in which there is 25 well data for creating suitable training image by the principal component analysis (PCA) method. In this study, MPS is successfully applied to facies modeling and the spatial continuity of facies is reasonably reproduced. The facies model verifies the reproduction of facies proportion in training image and wells. Also, five wells are used for the cross correlation of the facies model. The results indicate that the facies model shows a strong correlation with the facies of these five wells. Additional hard data, which is extracted from high confidence seismic data, is so useful for the improvement of the facies model.

Keywords: Facies, Seismic, Data Conditioning, PCA, MPS.

INTRODUCTION

Facies modeling is usually done by deterministic [1,2] and several stochastic methods [3-5]. Variogram-based stochastic methods cannot describe the spatial distribution of complex structures in heterogeneous reservoirs such as carbonate reservoirs. Features that cannot be modeled by traditional geostatistical methods can be modeled by object-based methods, but data conditioning is difficult. MPS is introduced to overcome the limitations of the variogram-based stochastic methods. MPS reproduces the nonlinear features in reservoirs by considering the relationship between multiple points at the same time [6,7]. MPS integrates the strengths of pixel-based and object-based methods [6,8,9]. It uses the flexibility of the pixel-based methods by modeling a pixel at a time; hence, data conditioning is easily accomplished, and it allows the reproduction of the facies shapes and patterns similar to object-based methods. For these reasons, MPS is introduced for the facies modeling of complex reservoirs and can be conditioned to hard and soft data.

This study focus on the facies modeling of heterogeneous carbonates reservoirs. In MPS, a

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training image is needed, so a small part of the oil field in the vicinity of simulation grid is used as the training image. Facies modeling is done by using the facies of ten wells, the probability of facies, and additional hard data. The facies is modeled by single normal equation simulation (SNESIM) algorithm and is cross validated by the facies of five wells.

Methodology

There are many statistical and geostatistical methods for facies modeling. In this study, PCA and MPS methods are used for facies modeling. SNESIM algorithm is introduced and discussed as a program, which is used by the MPS method.

PCA

PCA is mathematically defined as an orthogonal linear transformation, which transforms the data to a new coordinate system with the greatest variance by the projection of the data on the first axis. The second greatest variance is projected on the second axis, and so on [10]. PCA is one of the statistical multivariable methods, which reduces the dimension of data. By this method, it is possible to change many dependent variables to a few independent variables, which are called principal components. In summary, PCA involves the following steps [11]:

1- PCA requires N inputs and returns N linearly transformed outputs (eigenvectors), called principal components. Below formula is used for the transformation of the input data to the transformed outputs:

$$u = wx \tag{1}$$

where, u is m-dimensional projected vector, and x is the original n-dimensional data vector.

2- The m projection vectors, which maximize the variance of u (the principal axes) are given by the eigenvectors (e_1, e_2, … e_n) of the data set's covariance matrix S associated with the largest m eigenvalues. The above observed data covariance matrix is as follows:

$$S = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)(x_i - \mu)^T \tag{2}$$

3- The eigenvectors and eigenvalues can be found by solving the set of equations:

$$(S - \lambda_i I)e_i = 0, i = 1, \ldots, m \tag{3}$$

4- PCA ranks the PC's according to their contribution to the total variance of the dataset (determined by descending eigenvalues).

MPS

Variogram is a statistical tool describing the difference of a variable observed at any two spatial locations. The successful application of the geostatistical methods relies on the variogram. Different types of reservoir heterogeneities may produce a similar experimental variogram, as shown in Figure 1.

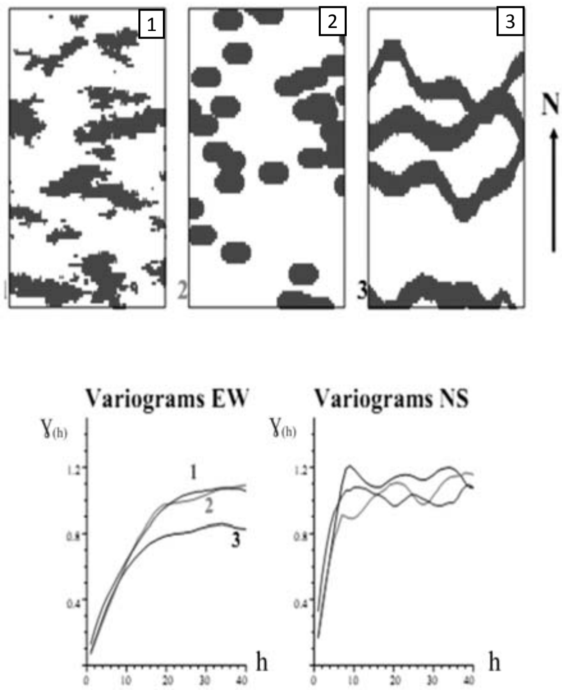

Figure 1: In this picture, there are three different geological phenomena. The variograms of these geological phenomena in EW and NS directions is plotted. The range and nugget of these variograms are so similar, so variogram cannot properly describe the geological heterogeneity [12].

The popularity of variogram-based geostatistics lies in the mathematical simplicity of the variogram model, not in its power to generate different types of geological models. MPS is a family of spatial geostatistical interpolation algorithms which are used to create conditional simulations of reservoir properties. MPS are able to honor well and seismic data. These algorithms require a training image to represent a spatial distribution of geological properties which is expected to be similar to the target property. The main idea of MPS is the description of spatial correlation of multiple points at the same time.

In MPS method, there are several pixel-based and pattern-based algorithms for complex geological structure modeling. Pixel-based algorithms such as SNESIM and pattern-based algorithms such as SIMPAT (simulation with patterns), FILTERSIM (filter-based simulation), DISPAT (distance-based pattern modeling), and CCSIM (cross correlation-based simulation) can be used for facies modeling. Strebelle developed the first multiple-point geostatistics algorithm of SNESIM for the simulation of discrete variables [13]. SNESIM uses a pixel-based equation simulation approach, which makes the conditioning to well and seismic data much easier than object-based modeling techniques. For improving the connectivity of a geological phenomenon, pattern-based algorithms have been developed. Arpat for first time introduced SIMPAT as a pattern-based MPS algorithm, which uses a similarity rule to find the most similar pattern to the conditioning data [14]. SIMPAT is a very time consuming and CPU demanding algorithm. Thus, Zhang introduced a new algorithm FILTERSIM, with the idea of summarizing multiple-point spatial patterns using a few general linear filters [15]. This pattern-based multiple point geostatistical algorithm can be used for the modeling of continuous and categorical variables. These summaries of patterns caused by filters reduce dimensions and all bins are pre-classified into a data tree structure, so this algorithm has a high speed and reduces memory demanding. After that, Honarkhah introduced DISPAT as a distance-based algorithm for modeling patterns in space, which improves pattern reproduction and continuity and reduces parameters, user interaction, and computation time [16]. The mentioned pattern-based algorithms require a huge data base, which cause more memory and CPU demanding. Thus, Tahmasebi introduced another pattern-based algorithm, which works based on cross correlation function and is called CCSIM [17]. This algorithm significantly improved the CPU time and RAM demanding. In this study, Petrel 2011 software is used for facies modeling of this carbonate reservoir. This software only uses SNESIM algorithm and does not employ the other algorithms.

SNESIM Algorithm

SNESIM represent “single normal equation simulation” and is an algorithm for the reservoir facies modeling. This algorithm is a pixel-based method which uses multiple point geostatistics and is combined with its sequential nature. It efficiently generates complex realizations such as sinuous channels. The idea behind SNESIM is very simple; each pixel node is simulated sequentially in a random order. Facies is drawn with conditional probabilities that are frequencies extracted directly from a given training image, which reflects a prior knowledge of the reservoir [18]. SNESIM is a sequential simulation algorithm, much in the style of well-known methods such as sequential Gaussian simulation and sequential indicator simulation [19,20]. It relies on the idea of simulating each grid cell facies or petrophysical property sequentially along a random path, where the simulation of cells later in the process is constrained by the cells earlier simulated along with well and seismic data. There are two main parts in the SNESIM algorithm. The first part is the construction of a search tree to store pattern proportions from training images. The second part is sequential simulation section, where simulated values are drawn based on these proportions. The algorithm corresponding to the simplest SNESIM implementation is given below [13]:

1- Define a multiple point template T_J to scan the training image.

2- Scan the training image using the multiple point template T_J and store the pattern proportions in a search tree object.

3- Assign available conditioning data to their nearest simulation node.

4- Define a random path visiting all locations to be simulated once and only once.

5- For each location *u* do the following:

a. Determine the current conditioning data event (d_n) within the template T_J

b. Calculate the conditional probability distribution based on the pattern proportions from the search tree.

$$\text{Prob}\left\{S(u)=s_j \mid d_n\right\} = \frac{\text{Prob}\left\{S(u)=s_j \text{ and } S(u_\alpha)=s_{j,\alpha};\alpha=1..n\right\}}{\text{Prob}\left\{S(u_\alpha)=s_{j,\alpha},\alpha;\alpha=1..n\right\}} \quad (4)$$

c. Randomly take sample from this conditional probability distribution and assign this simulated value to location *u*. Treat the simulated value as conditioning data.

6- Repeat step 5, until all nodes in the grid are simulated.

RESULTS AND DISCUSSION

Facies Modeling

The case study is one of Iranian southwest oil fields. A part of the oil field, which is located on the northwest nose of anticline, is used for facies modeling. In this oil field, main reservoir is Asmari formation, which is composed of limestone, dolomite, sandstone, and shale. Asmari formation is divided to five geological zones, in which upper zones are mainly composed of limestone and dolomite, and lower zones are mainly composed of sandstone and shale. There are forty wells with petrophysical logs and core data. The facies of these wells are interpreted by petrophysical logs and core description. These facies are clustered into four main classes, namely dolomite, limestone, sandstone, and shale (Figure 2). Also 3D seismic data and seismic attributes of Asmari formation are available for facies modeling.

Training Image

Training image is a three dimensional reservoir picture which conditioned to any local reservoir data. It is sufficient to contain relative dimensions and, most importantly, relevant geological features [13].

The training image for carbonate reservoirs is a 3D conceptual model of the reservoir, containing information about facies distribution in space and their relations with respect to each other. Training images can come from several different sources such as interpreted outcrop photographs, geologists sketch, and so on. Moreover, the training image can be generated by using unconditional object-based [21,22,23,24] or process-based simulations [25]. An accurate training image is one that combines different sources of data (geology, geophysics, and reservoir data) to reflect a reservoir features. The most likely source of data for creating a training image would be a part of the oil field near the simulation grid.

For this reason, the training image is selected from a small part of this oil field, which is in the vicinity of the simulation grid. The training image is located on the northwest nose of anticline with a high density of wells, the facies proportion of which is similar to wells in the simulation grid (Figure 3 and Table 1).

The relation between seismic attributes and facies is analyzed. Nine seismic attributes, which are related to facies, are used for facies modeling.

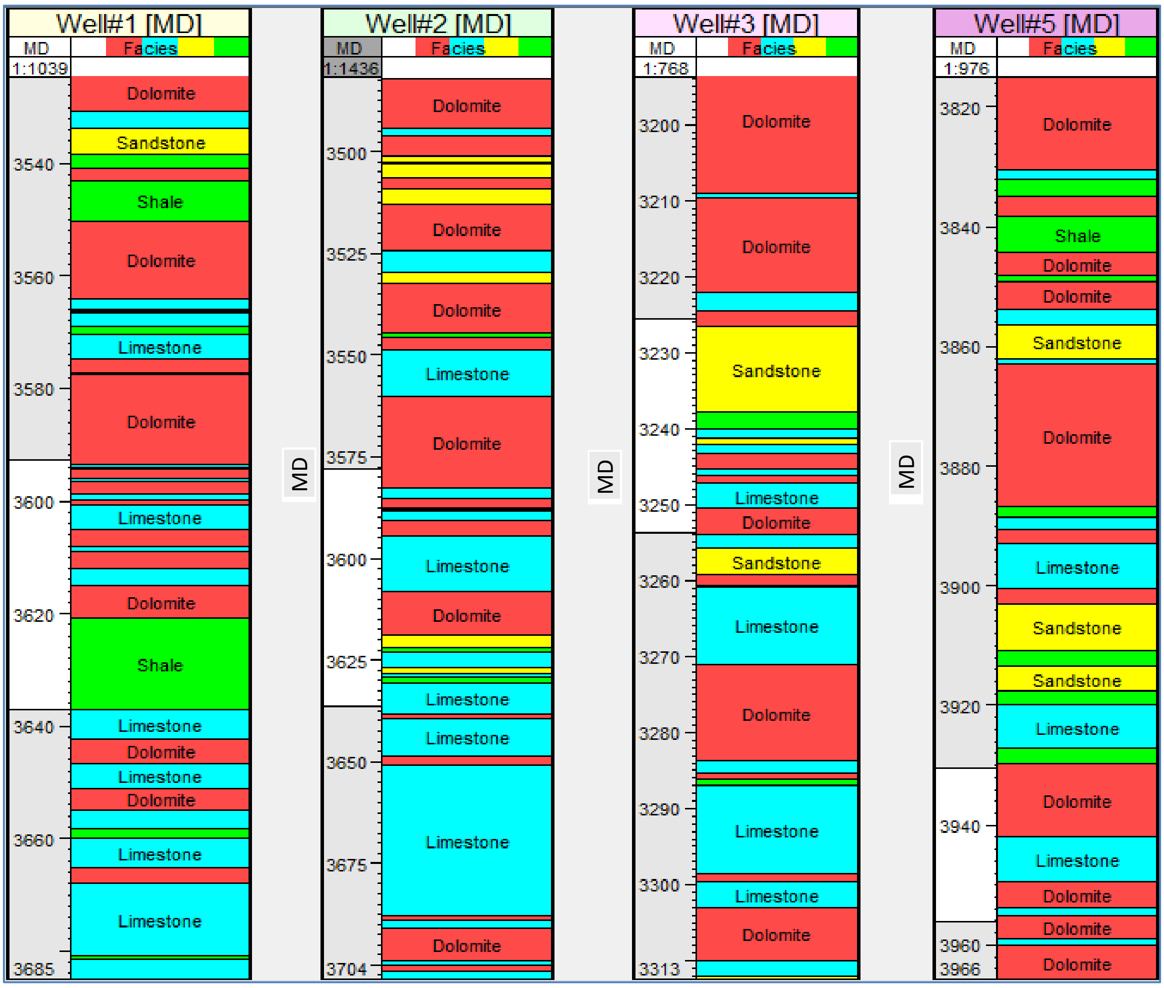

Figure 2: Facies of four wells which is interpreted by petrophysical well logs and core description.

Table 1: Facies proportion of wells in the training image and simulation grid.

Facies Type	Wells (training image)	Wells (simulation grid)
Dolomite	23.99	24.67
Limestone	33.98	40
Sandstone	21.47	18.05
Shale	20.56	17.27

These nine seismic attributes are envelope, instantaneous frequency, flatness, original amplitude, chaos, relative acoustic impedance, attenuation, dominant frequency, and instan taneous phase (Figure 4).

In Petrel software, the PCA method is used for creating the training image (facies modeling). Facies of twenty five wells and nine seismic attributes are used as the input data. By the PCA method, the principal component analysis spreadsheet is produced. Five major principal components are used as the input data for training the estimation model. The training image is modeled by a 500-time repeat, a 5% error limit, and a 30% cross validation. The facies of this training image is modeled by PCA, which honors seismic attributes and facies of twenty five wells (Figure 5). The correlation of this training image with these 25 wells is 0.66 (Table 2).

Table 2: Facies proportion of wells and the training image modeled by PCA.

Facies Type	Wells (training image)	Training Image Modeled by PCA
Dolomite	23.99	19.27
Limestone	33.98	36.77
Sandstone	21.47	23.26
Shale	20.56	20.71

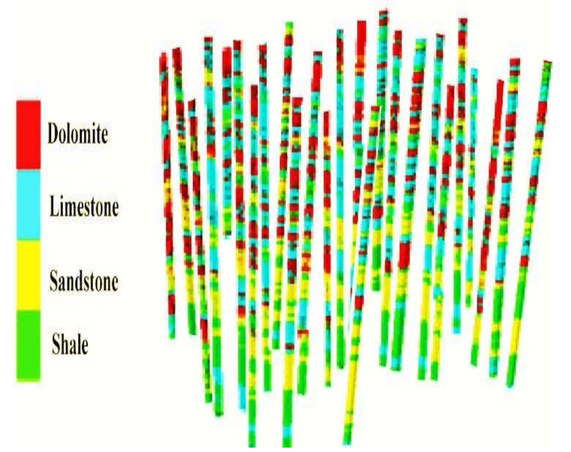

Figure 3: Dense hard data used for creating the training image.

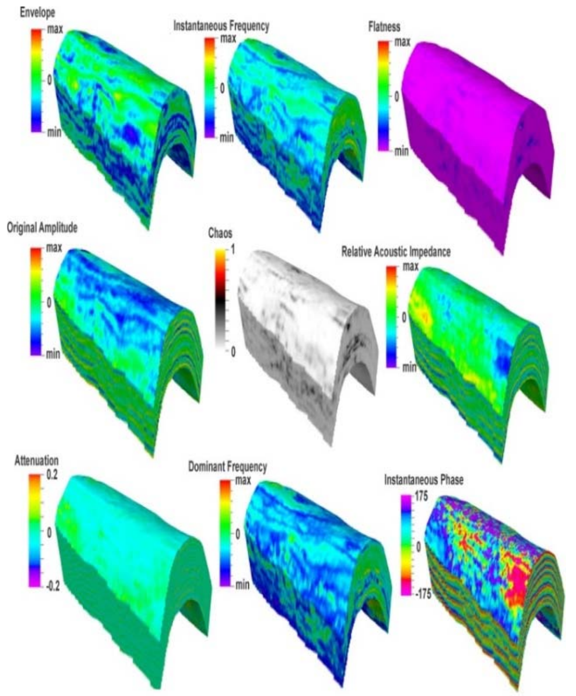

Figure 4: Seismic attributes used for facies modeling.

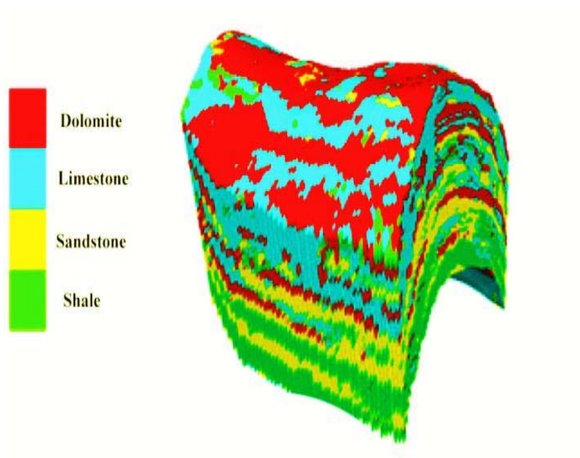

Figure 5: The training image modeled by PCA method.

Facies Modeling by MPS

The facies model should be conditioned by hard and soft data, so wells and three dimensional seismic data are used as hard and soft data respectively. The term hard data is used to emphasize the fact that the modeling method should exactly reproduce this data value at its location [14]. In this study, the facies of ten wells are used as the hard data (Figure 6).

For every facies, a soft probability property can be determined. The soft data are to be used only as a guide to modeling and are not expected to be reproduced exactly [14]. Seismic attributes, which are used for facies probability modeling, are shown in Figure 4. The probability of facies is modeled by PCA and seismic attributes (Figure 7). Additional hard data is extracted from high confidence seismic data. Additional hard data can be created from seismic and calculated from high confidence soft data. For extracting hard data, 3D acoustic impedance, effective porosity, and gamma ray are used and it is truncated to show facies in specific ranges (Table 3). These ranges are checked in wells and they are completely correlated with wells facies. The 3D additional hard data, which are calculated from 3D geological model, are shown in Figure 8.

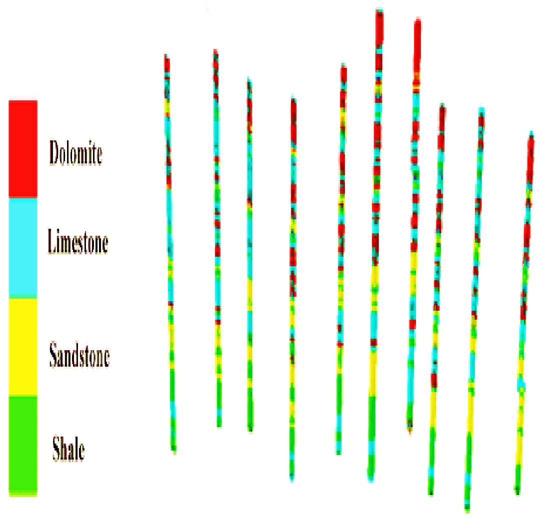

Figure 6: Hard data for facies modeling by MPS.

Table 3: Ranges of acoustic impedance, effective porosity, and gamma ray for different facies.

Facies	Acoustic Impedance (gr/cm^3.S)	Effective Porosity (V/V)	Gamma Ray (CGR) (GAPI)
Dolomite	>16000	-	-
Limestone	<12800 and >13500	-	-
Sandstone	<9100	>0.07	<50
Shale	-	<0.07	>85

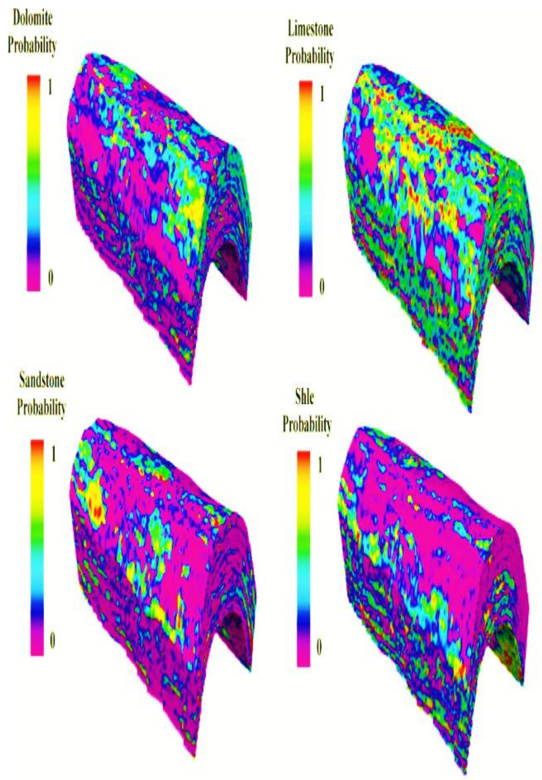

Figure 7: 3D probability model of four facies.

The MPS simulation program SNESIM is used to generate facies models honoring the hard data, additional hard data, and soft data. For facies modeling by MPS, at first, the training image is preprocessed to extract all patterns. For pattern extraction, an elliptical template with dimensions of (5 by 5 by 3 meters) and 32 informed nodes is used. Then, these patterns are used as building blocks within a sequential simulation algorithm. Five MPS realizations with elliptical template and data conditioning are generated in the simulation grid. MPS simulation for five realizations took approximately one hour. The facies realization is shown in Figure 9.

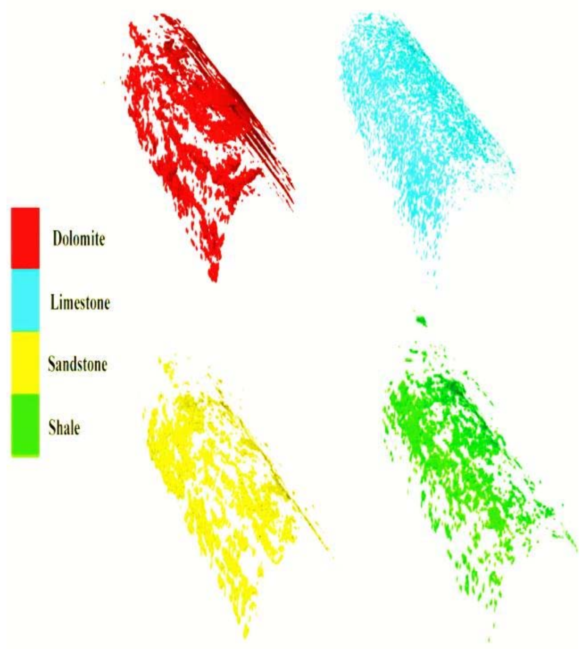

Figure 8: Additional hard data of four facies.

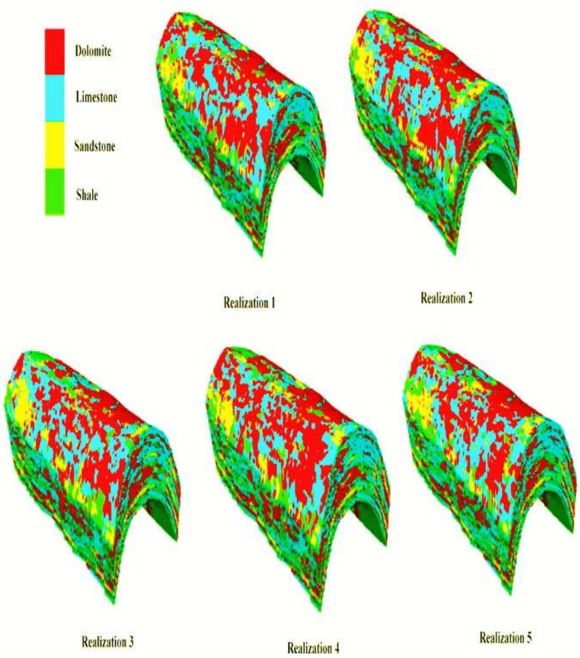

Figure 9: Five realizations of 3D facies model by MPS method.

Validation of Facies Model

There are a number of methods to validate facies models. Facies modeling by MPS is validated as follows:

1- Reproduction of histogram: The histogram of facies model and wells should be equal or close to each other.

2- Reproduction of the vertical variogram model (or reproduction of facies proportions per layer): facies proportions for each layer in facies model and wells should be equal or close to each other.

3- Blind test or cross correlation: The facies model should show a good correlation with the facies of wells, which are not used in the facies modeling.

The facies proportions of wells and MPS realizations are compared. As it is shown in Table 4, the facies proportions of wells are successfully reproduced. In other words, the histogram of wells facies is successfully reproduced. It is concluded that facies model by MPS method properly conserve the facies histogram of the wells. Furthermore, facies proportions of all the layers in the wells, the training image, and MPS model are compared. The facies proportions in the wells and the training image are successfully reproduced (Figure 10), so the facies of this carbonate reservoir is modeled properly by an MPS method.

For recognizing the best realization and the accuracy of MPS facies modeling, the facies models are cross correlated with five wells, which are from all the parts of the simulation grid, and are not incorporated in facies modeling) (Figure 11 and Table 5). The correlation of MPS realizations facies with these wells facies are shown in Table 6. The best correlation between MPS realizations facies and wells facies is 0.63.

Table 4: Facies proportion of the MPS realizations, the wells, and the training image.

Facies type	MPS1	MPS2	MPS3	MPS4	MPS5	wells	Training image
Dolomite	24.19	24.37	24.41	24.34	24.59	24.67	19.27
Limestone	42.01	42.05	41.82	41.73	42.08	40	36.77
Sand	17.27	16.92	17.25	17.11	16.72	18.05	23.26
Shale	16.45	16.56	16.42	16.72	16.51	17.27	20.71

Table 5: Facies proportion of five wells.

Facies Type	Facies of five wells (%)
Dolomite	36.52
Limestone	29.70
Sandstone	18.47
Shale	15.31

Table 6: Correlation coeficient of facies in the MPS realizations and five wells.

Realizations	Correlation with facies of five wells
MP1	0.6318
MP2	0.6097
MP3	0.5935
MP4	0.5693
MP5	0.5764

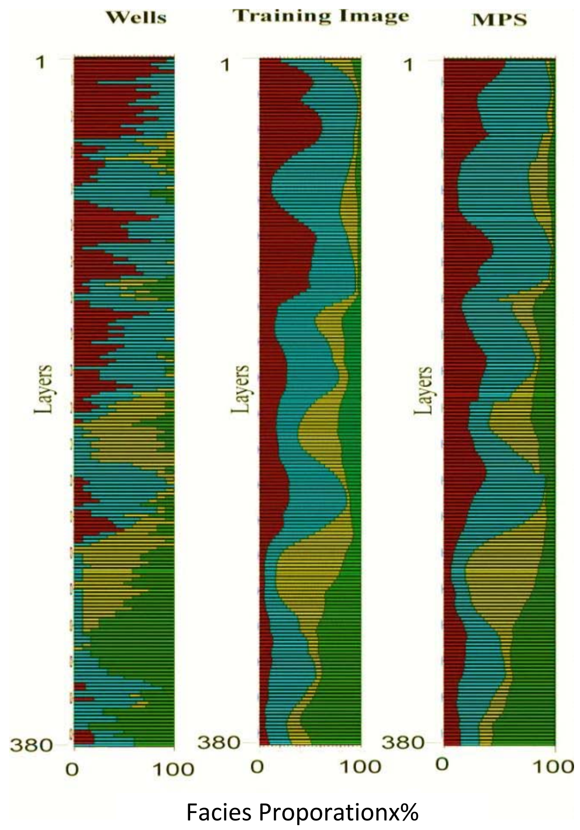

Figure 10: Facies proportions of the wells, the training image, and MPS in all the layers.

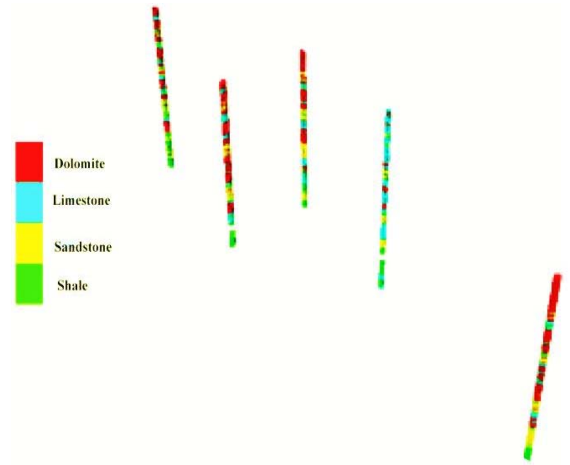

Figure 11: Five wells for the validation of facies models by MPS.

CONCLUSIONS

This study is one of the first studies applying MPS method to carbonate reservoirs. In this study, the MPS is successfully applied to the facies modeling of the heterogeneous carbonate reservoir. The training image is properly produced by PCA method and the integration of petrophysical, geological, and seismic data. Additional hard data are used in facies modeling by MPS method. This additional hard data were so helpful, so it is one of the strength points of MPS with respect to other geostatistical methods. The facies modeled by MPS is validated by the facies of five wells and the histogram of well data. The good correlation between facies model and five wells and the reproduction of facies histogram in the wells show that the facies is properly modeled by MPS. It is recommended to use object-based methods for creating the training image in channels and fluvial reservoirs. The algorithms of MPS method often require large CPU and RAM demands, so it is recommended to develop an algorithm to use lower CPU and RAM resources.

NOMENCLATURE

N	: Number of input and output data
U	: *m*-dimensional projected vector
X	: Original n-dimensional data vector
M	: Projection vectors
$(e_1, e_2 \ldots, e_n)$	: Eigenvectors
S	: Covariance matrix
λ_i	: Eigenvalues
T_J	: A multiple point template T_J
d_n	: Conditioning data event

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