Integrated data analysis using electrofacies and seismic attribute for reservoir modeling

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Abstract

Conventional reservoir characterization based only on the statistics of reservoir properties is hard to apply to immature exploration fields with limited number of wells. In that case, integrated analysis of all the available field data is necessary to minimize the uncertainty of reservoir property estimation.

To extend measured properties from the wellbore to the entire reservoir, this research proposes a practical method based on three steps of integrating analysis: detecting and classifying electrofacies from well logs, estimating petrophysical property using well logs and core data, and spatial modeling from seismic attribute.

We present initial results of the workflow using a field dataset. Electrofacies detection is carried out, and the structure to predict properties using artificial intelligence training is established. Next, well log data upscaled to the seismic resolution will be used in the correlation analysis between acoustic impedance and various reservoir properties to tackle the problems of scale discrepancy.

1. Introduction

Integrating information from a variety of sources into reservoir models is a significant challenge in reservoir forecasting, especially in early development stages with limited information. Since obtained data such as core, well logs, and seismic measurements have different scales of resolution, reconciling multi-scale data for spatial modeling of reservoir properties is most important. Thus it is essential that reservoir models preserve small scale property variations observed in well logs and core measurements, as well as capture the large-scale structure and continuity observed in global measures from seismic data.

In general, seismic data has been used to discriminate strata, find out structural and stratigraphic reservoirs, and indirectly predict the reservoir fluid using local

amplitude or amplitude-versus-offset anomaly. Recent studies have focused on estimating reservoir properties from the relation between properties and various extracted seismic attributes (e.g. Azalgara, 2001; Reeves et al, 2002). Table 1 shows the definition and relationship of these attributes (Artun et al, 2005). Since acoustic impedance has higher correlation with sonic log and density log from well logging data, it is widely used to make a relationship to characterize reservoir properties (Torres-Verdin, 2000; Anjos and Zucchi, 2001).

Therefore, data integration analysis for reservoir characterization is a process to extend our obtained reservoir properties such as porosity and permeability from core measurement to the seismic data scale. As shown in Figure 1, this research focuses on three steps of the integration methodology: electrofacies detection from well logs, estimating petrophysical property using well logs and core data, and seismic attribute-guided spatial modeling.

Table 1: Various seismic attributes and their characteristics (Artun *et al*, 2005)

Seismic Attributes	Characteristics & Indicator
Amplitude	Measure of the strength of the reflected signal. Indicates changes in physical properties of lithological entities. It can sometimes be used to detect gas presence.
Instantaneous Phase	Phase angle range from -180 degrees to +180 degrees. Envelope and phase are combined as polar components of a trace signal.
Average Energy	Highlights stratigraphic detail through energy fluctuations across traces
Envelope	Represents the reflection strength. It relates directly to the acoustic impedance contrasts.
Acoustic Impedance	Product of P-wave velocity and density. It is highly related to the physical properties of formation.
Frequency	Describes how long it takes the phase to complete 360 degrees of rotation.
Paraphase	The instantaneous phase with predictable trend removed. As such, it assists visualizing the structural picture because phase tracks geologic boundaries.
Hilbert Transform	This amounts to 90-degree phase rotation. Amplitude and Hilbert transform are combined as Cartesian components of a trace signal.

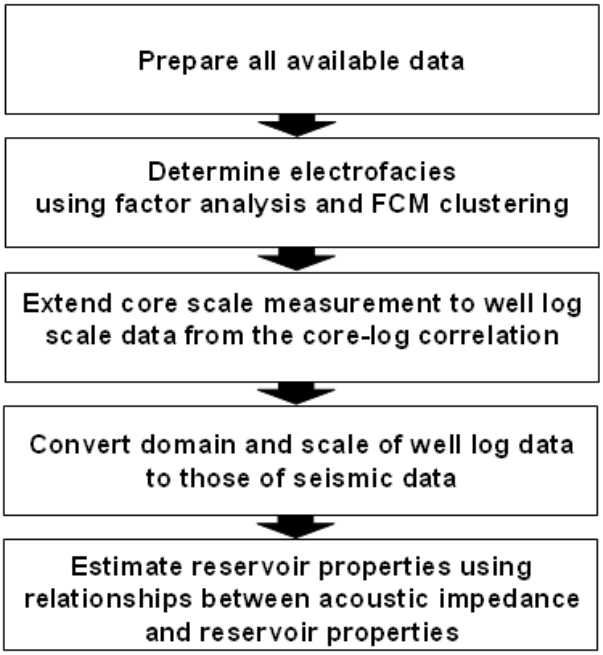

Figure 1: Flowchart of integrated analysis for reservoir characterization

1.1. Estimation of petrophysical property

Reservoir properties such as permeability and porosity play a key role not only for designing facilities but also for optimizing the production. However, since well-logs cannot directly measure the permeability, the estimation for these unknowns is difficult and complex process (Mohaghegh et al., 1997; Finol et al., 2001). Artificial intelligence methods like neural network and a fuzzy logic have been proposed to improve predictability by using advanced pattern recognition. Among theses, fuzzy modeling has been successfully applied to various fields, and showed superior prediction results than others such as empirical equations, regression model and artificial neural network model (Cuddy, 2000; Shokir, 2004; Taghavi, 2005; Abdlraheem et al., 2007). It is efficient for figuring out the general trend since it deals with the interrelationship between core properties and only among a few strongly correlated variables such as density log or gamma ray log. However, it often shows unreliable predictions such as strong oscillations and extreme outliers in the case of highly heterogeneous reservoir.

To predict the unknown petrophysical series more reliably, this paper proposes a

new model integrating electrofacies characterization into fuzzy inference system. The estimation process is divided into two phases: the pre-treatment of well logs for detecting electrofacies, and numerical prediction using fuzzy model. First, factor analysis and three-dimensional Fuzzy C-Means clustering (FCM) are used to characterize and identify electrofacies. Next, a fuzzy model is constructed to predict porosity and permeability using calculated factor scores and electrofacies in each log-interval. From this process, we can generate petrophysical properties at the well log scale, and detect electrofacies which explains the distinct responses of well logs and diagenetic characteristics.

1.2. Seismic attribute-guided spatial modeling

Acoustic impedance derived from seismic data is a rock property, and it can provide important insights into reservoir parameters such as porosity, lithology, and fluid content. Direct measurements of acoustic impedance are available from sonic and density well logs. Seismic inversion, a process of converting seismic data into relative impedance, provides estimates of relative acoustic impedance away from the well locations. Because absolute acoustic impedance can be related to other rock properties, the inverted relative seismic impedance could be used to predict these properties away from the wells if the missing low frequencies could be reliably calculated (Hansen et al, 2008).

Therefore, this research focuses on this relation of acoustic impedance and related well logs. Acoustic impedance of reservoir is estimated by inversion of each seismic trace, and it is linked to correlation analysis with well log data. Based on this correlation and detected electrofacies information, we can generate reservoir properties of each cell based on this acoustic impedance distribution.

2. Theoretical Background

2.1. Electrofacies

The distinct log responses in the formation can be defined as electrofacies that can be correlated with actual lithofacies identified from cores, based on depositional and diagenetic characteristics (Serra and Abott, 1980). The importance of electrofacies characterizations in reservoir description and management has been widely recognized. This classification does not require any artificial subdivision of the data population but follows naturally, based on the unique characteristics of well log measurements reflecting minerals and lithofacies within the logged interval. A combination of principal components analysis, model-based cluster analysis and discriminant analysis is used to characterize and identify electrofacies types (Moline and Bahr, 1995; Lee *et al*, 2002). The method used to perform the electrofacies classification is based on attempts to identify clusters of well log responses with

similar characteristics. In this research, it is a two-step procedure consisting of factor analysis and FCM clustering.

2.1.1. Factor analysis

Factor analysis is one of practical tools to extract the key factors from all observed variables that are accompanied by some latent characteristics. In addition, it fits a model to multivariate data for determining the interdependence. Factor analysis detects the characteristics that strongly affect the response from the population, and distributes them in n-dimensional space according to the factor scores (Gorsuch, 1983; Love *et al* 2004).

The individual variable can be expressed as a linear-combination of the factors. The correlation between the factor and the observed variables is demonstrated as the loading. Factor model can be defined as the variable matrix (X) that consists of the matrix of loadings (L), the factor matrix (F), and the diagonal matrix (ψ) as shown in Eq. (1)

$$X = LF + \psi \tag{1}$$

The element of ψ refers to "specific variance", the distance with common factor. The individual factors are obtained through the principal component factoring. The principal component (P) is the projection of the variable (X) on to the eigenvector basis (Λ) in Eq. (2).

$$P = X^t \Lambda \tag{2}$$

The factor score, the element in F , can be obtained from $F = P / \sigma_{PC}$ where σ_{PC} is the standard deviation of principal component. To distinguish each factor more clearly, the Varimax rotation is applied (Eq. (3)).

$$\begin{aligned} &\max \sum_{k=1}^{m} \sum_{j=1}^{p} (l_{jk}^2 - l_k^2)/T \\ &\text{subject to} \sum_{k=1}^{m} l_{jk}^2 = \text{constant}, \quad j = 1,2,\cdots,p \end{aligned} \tag{3}$$

In Eq. (3), $l_k^2 = \sum_{j=1}^{p} l_{jk}^2 / t$, t is an element of T (the rotational matrix) and l_{jk}^2 is an element of L the loading. As a result of Eq. (3), the factor scores are obtained.

2.1.2. Factor- scores clustering using Fuzzy C-means(FCM)

The objective of factor-scores clustering is to identify the data groups from the population to produce a concise representation of a system's behavior. FCM is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade (Bezdek, 1981; Varshavsky et al., 2005).

It is based on minimizing the objective function shown in Eq. (4).

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2, \qquad 1 \le m < \infty \tag{4}$$

In Eq. (4), m is any real number greater than 1, u_{ij} is degree of membership of x_i in the cluster j , c_j is the center of the cluster, and $\|*\|$ is any norm expressing the similarity between any measured data and the center.

Iterative optimization carries out fuzzy partitioning until reaching the maximum value of u_{ij} in Eq. (5).

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{2/(m-1)}}, \qquad c_j = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{5}$$

2.2. Adaptive neuro-fuzzy inference system

Fuzzy logic is conceptually based on the naturalness. The inference system does not divide all variables into white or black like a dichotomy, but still retains within them a level of fuzziness. The process of fuzzy modeling involves membership functions, logical operations, and if-then rules. From those structures, there are two types of fuzzy inference systems; Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined (Mandami and Assilian, 1975; Sugeno, 1985; Jang et al., 1997). The prediction of permeability is

carried out by using the Sugeno-typed fuzzy inference system and the Adaptive Neuro-Fuzzy Inference System(ANFIS) in Matlab™ (Jang, 1993; Blanchet and Charbit, 2006).

Figure 2 is an example of ANFIS modeling. ANFIS establishes a relationship between the inputs and outputs from the training data set, and checks predictability using validation data set. In the Figure 2, blue points are validation data set and red are prediction of the trained fuzzy structure. Inputs are the score of three factors and outputs are core measurements such as porosity and permeability.

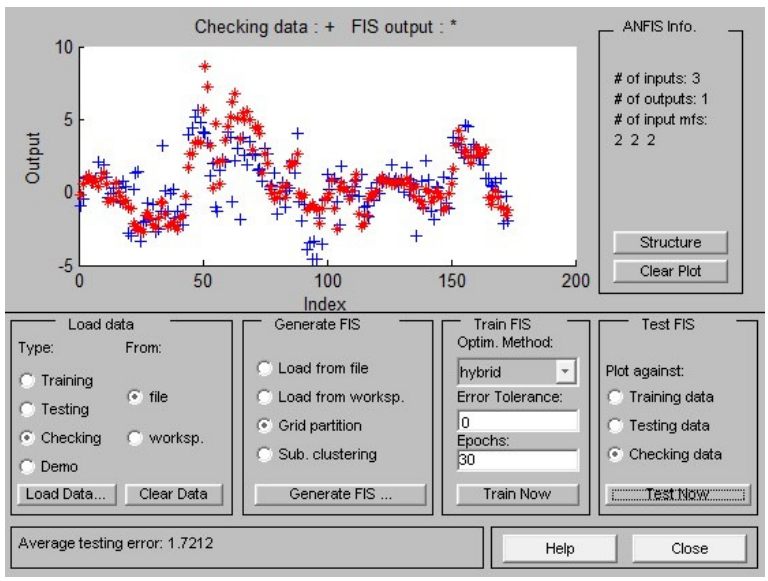

Figure 2: This figure shows the ANFIS processing in Matlab. After loading dataset, sequentially clustering and training are carried out.

3. Field Application

The data used in this study are from offshore Equatorial Guinea, West Africa. This is a comprehensive dataset from channelized turbidite sequences, which were deposited in offshore Equatorial Guinea (Rio Muni basin), West Africa. Figure 3 shows the location of the study area. The dataset includes post-stack seismic data, well logs, digital core images and detailed core descriptions. Table 2 is detailed core descriptions (Dutta, 2009), and figure 4 shows these available data. In this field, we have two main wells and one bypassed well as the Figure 4 shows. The range of red color means well logging regions and purple bandwidth shows core measurements. In addition, thin-sections, XRD, SEM and laser particle size analysis data are

available in selected intervals at key wells. This field is an ideal setting for this research because it has only three exploring wells and limited core measurements. We can apply our methodology to predict entire reservoir properties using all available data.

Table 2: The sediments characteristics and depositional settings (Dutta, 2009)

Lithofacies	Sediment characteristics
Lithofacies-1: Thick-bedded to massive sandstone	Beds>20 cm thick
Lithofacies-2: Interbedded, thin-bedded sandstone and mudstone	Beds 2-20 cm thick, >20% sandstone
Lithofacies-3: Interbedded, thin-bedded sandstone and mudstone	Beds <2cm thick, usually <20% sandstone
Lithofacies-4: Carbonate-cemented sandstone	Diagenetic
Lithofacies-5: Conglomerate and breccia	30-60% mudstone clasts suspended within coarse to very coarse grained sandstone
Lithofacies-6: Mudstone	<10% sandstone interbeds

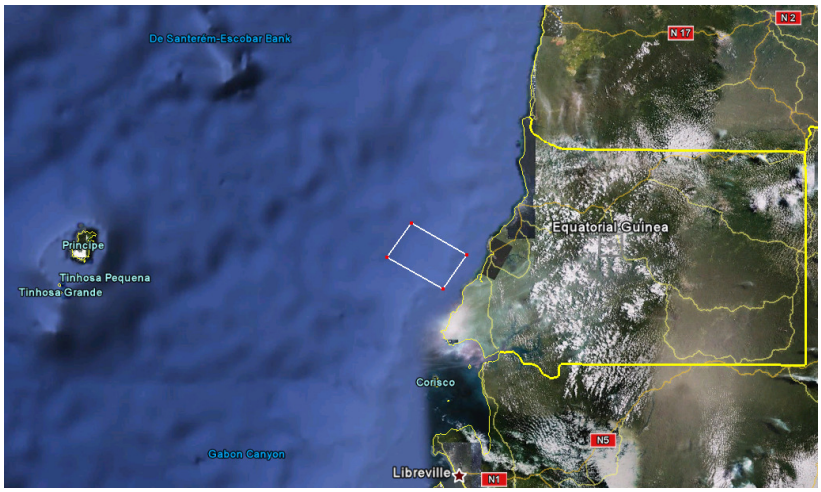

Figure 3: Location of the study area (white rectangle) in offshore Equatorial Guinea, West Africa.

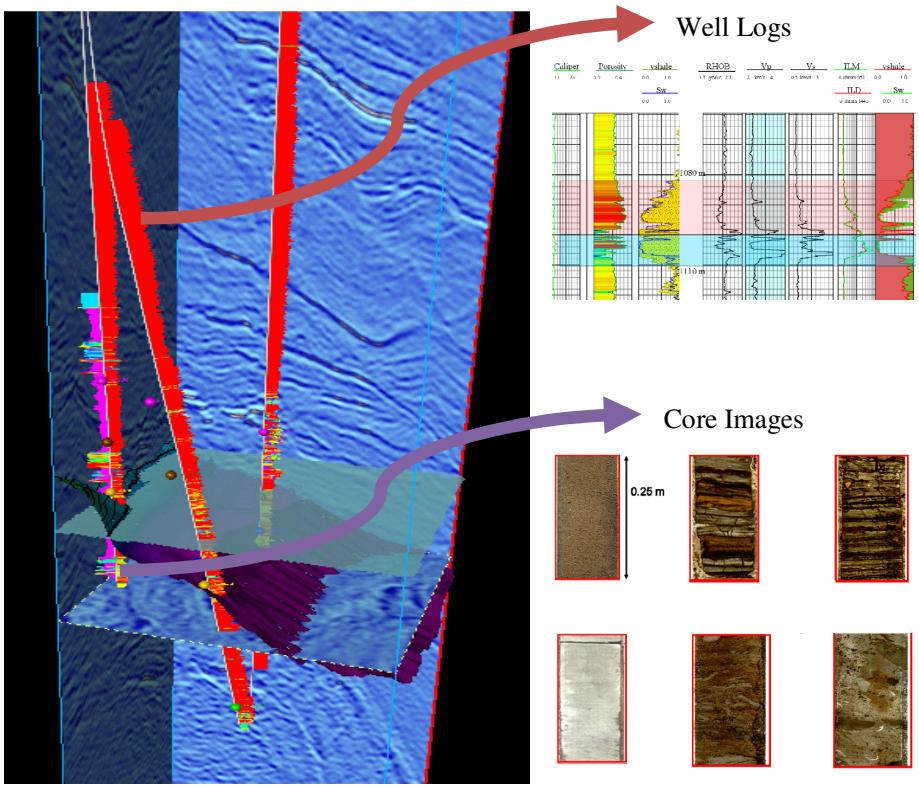

Figure 4: Post-stack seismic data (blue background), well logs(red), and digital core images (Dutta, 2009)

4. Discussion

Table 3 is the well logging information used in this study. Conventional eight logs were extracted from the data set. Figure 5 shows the scree plot of the eigenvalue related to each principal component and Table 4 summarizes the total variance explained. From the cumulative variance up to 80%, is explained by three main factors, and it represents most of the diverse characteristics. As a result of analyzing the latent characteristics, the correlation structure can be established in Table 5 and Figure 6, which shows the weight of input data on the factor.

Based on analyzing the well log information, FCM defines eight distinct clusters. These clusters, referred to as electrofacies, represent pseudo lithological differences. The scores according to three main factors at each depth are distributed in 3D space, and optimal clustering number is determined by Fukuyama-Sugeno differentiation index (Figure 7). Figure 8 is the result of the FCM classification for electrofacies. FCM defined eight different clusters (i.e. electrofacies) based on this distribution. Through proposed electrofacies characterization, Figure 9 shows classification results of petrophysical properties. It will be compared with core lithology descriptions and

used in property prediction using ANFIS modeling which is proposed before.

After these electrofacies determination and prediction modeling, upscaling of well logs to the seismic resolution and acoustic impedance inversion will be performed as Figure 10 shows conceptually. Correlation analysis between inverted acoustic impedance and sonic logs in wellbore would be a bridge to link each other. Also, correlation between electrofacies and the other seismic attributes will be tested to figure out more reliable reservoir characterization. This study will be continuously performed and tested based on the obtained field data.

Table 3: Obtained logs and core sample data from well A1

Well A1	Well logs	Core
1: GR 2: NPHI 3: RHOZ 4: AHT10 5: AHT30 6: AHT90 7: DTCO 8: HCAL	5412 samples	662 samples

Table 4: Principal component and its variance to determine the main factors

Component	Eigenvalue			Decision
	Eigenvalue	Variance (%)	Cumulative variance (%)	
1	3.506	43.829	43.829	Selected
2	2.038	25.474	69.302	
3	0.838	10.475	79.778	
4	0.695	8.682	88.460	Ignored
5	0.641	8.007	96.467	
6	0.117	1.462	97.929	
7	0.089	1.113	99.042	
8	0.077	0.950	100.000	

Table 5: Correlation structure between the input data and the main factors

Well logs (input data)	Factor		
	1	2	3
GR	0.235	-0.141	**0.929**
NPHI	**0.857**	-0.208	0.309
RHOZ	**-0.949**	0.075	0.097
AHT10	-0.055	**0.890**	-0.225
AHT30	-0.054	**0.926**	-0.210
AHT90	-0.064	**0.727**	0.139
DTCO	**0.924**	-0.110	0.196
HCAL	0.654	0.074	0.114

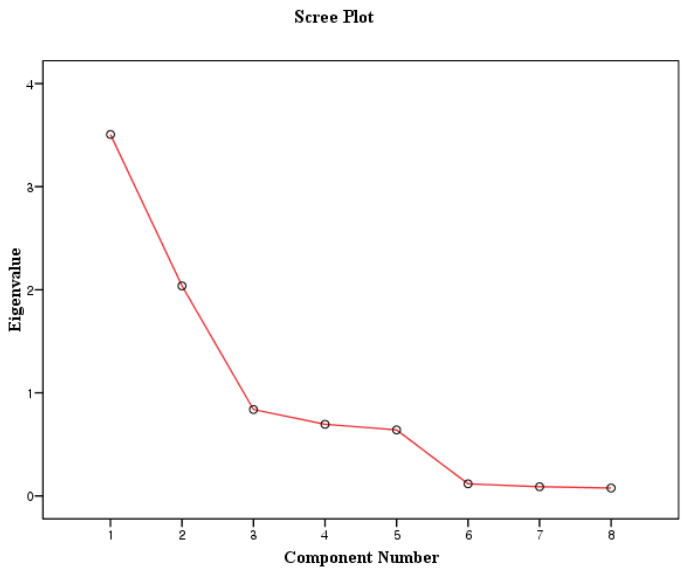

Figure 5: Scree plot

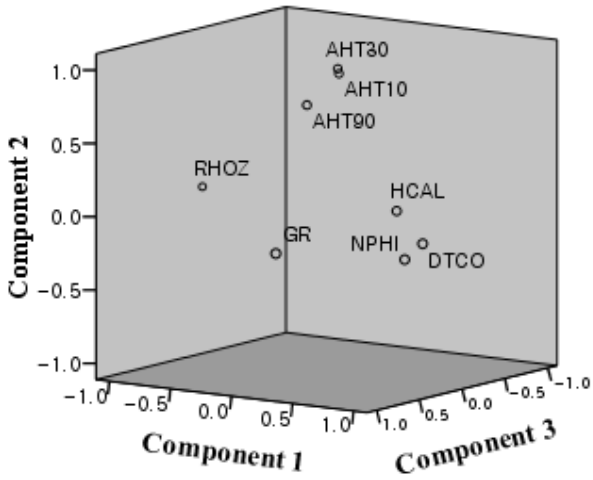

Figure 6: Components plot in rotated space

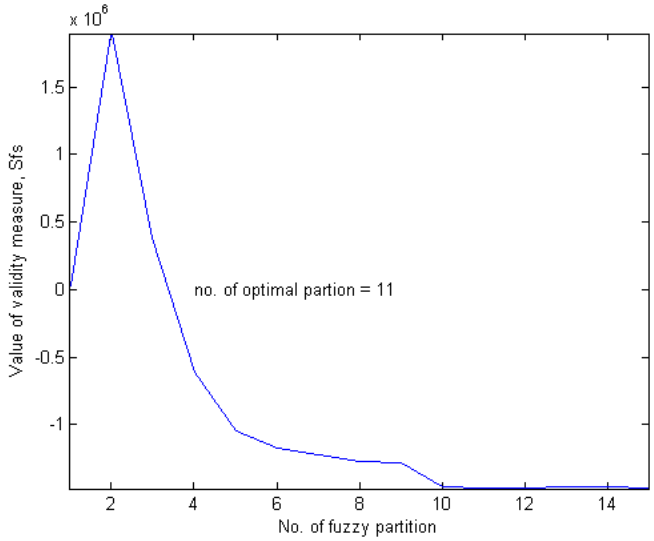

Figure 7: Optimal number of partition using Fukuyama-Sugeno differentiation index is eleven clusters. However, using too many clusters can be ineffective to reflect real reservoir lithology. Hence, it is assigned to use eight clusters in this paper.

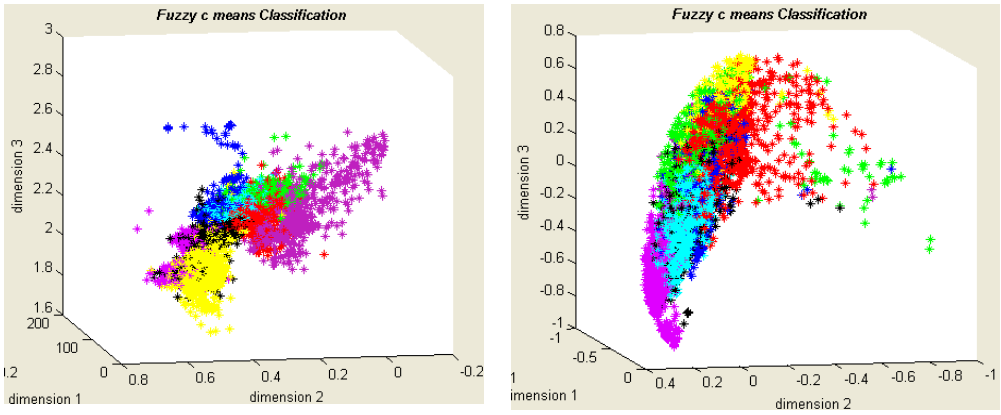

Figure 8: FCM classification for electrofacies detecting (left) This shows the result of basic classification using three main factors' score distribution, and (right) figure is the results of clustering after the singular value decomposition.

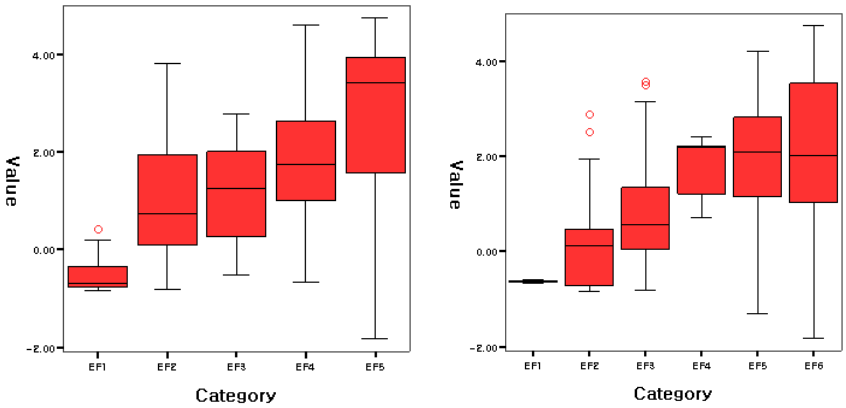

Figure 9: Permeability distribution in each electrofacies (left) FCM clustering results and (right) kmean clustering distribution. These permeability distributions are based on log scale value.

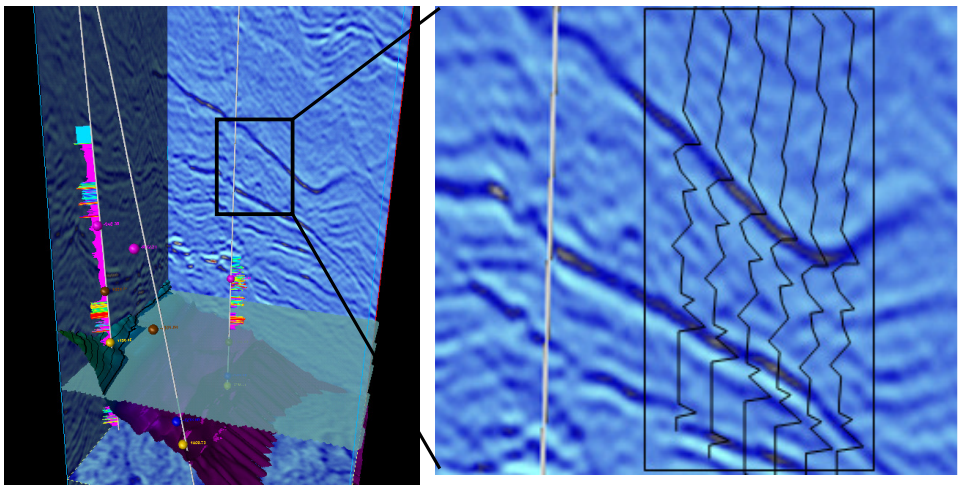

Figure 10: Conceptual model for seismic attribute-guided spatial modeling. The vertical lines represent inverted acoustic impedance according to seismic traces, and each line would be analyzed by correlation analysis of well logs. Since core-calibrated well logs include petrophysical property information, correlation between acoustic impedance and logs will be used in property generation for the whole reservoir.

5. Acknowledgements

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