geoconvention
Calgary • Canada • May 7-11 2018

Electrofacies classification of Horn River Shale by Multi Resolution Graph-based Clustering

Ju hwan Woo[1], Chul woo Rhee[1], Jae hwa Jin[2]*
1: Chungbuk National University, 2: Korea Institute of Geoscience and Mineral Resources.

Summary

Classification of lithofacies is an important step in reservoir characterization. The geological factors affecting hydraulic fracturing are the geomechenical properties, which are related to the mineral composition of rocks. Advanced log types (e.g. PNS, ECS) represent the mineral composition of the rocks. Constructing a more sensible electrofacies requires training data, which integrate quantitative mineral composition of core samples with advanced log data. There have been many suggestions for the statistical algorithm to classfy electrofacies. The Multi Resolution Graph-based Clustering (MRGC) used for the electrofacies classification of Horn River shales.

Introduction

Lithofacies are the most important parameters of the reservoir, and represent a meaningful unit with a certain range of porosity and permeability. Such a useful lithofacies can result from conventional core description combined with well log data because the log data are related to petrophysical parameters including porosity, permeability and water saturation. This study suggests that the pattern recognition method would be useful for the integration of analyses of the wireline log and core data. The main purpose of this study is to quantify and describes the lateral and vertical variability of the composition of the Horn River shale at well log scale. Understanding the spatial distribution of the rock properties within a formation is essential in exploration and development of shale resources.

Theory and/or Method

The MRGC method automatically determines the number of suitable clusters after analysis without a priori assumptions. It generates consistent clusters for data sets of extremely unbalanced sizes. This method allows the analyst to benefit from the complex and highly contrasting data structure revealed by crossplot and gives the sedimentological information. The module of Facimage in Geolog was used to enhance self-organizing maps and a neuron spilt method for cluster analysis. High resolution electrofacies model is contruct with suitable parameter. The MRGC log-predicted model trained with core-driven lithofacies and constrain for each member. It is applied to construct a high resolution electrofacies model with 33 clusters. 33 clusters are then grouped into six clusters to match the core facies model. MRGC enables adjusting variable parameters, which selects Mahalanobis metric and 6 initial neurons for CFSOM.

Lithofacies from core and advanced log

Six lithiofacies were identified and interpreted, based on the sedimentology and mineralogy data of core intervals. They were defined on the basis of texture, rock fabric (bedding style), color, and composition. In terms of composition XRD analysis and ECS log data were incorporated to quantify mineralogical abundance within each lithofacies. Faintly laminated siliceous mudstone (FLSM) and Homogeneous siliceous mudstone (HSM) were characterized by dark gray color with higher QFM and TOC content (Avg 3.35, 4.12%) than other lithofacies. The high QFM content affected hydraulic fracture stimulation and the TOC content was related to the amount of gas. Therefore, these two shale facies tend to be brittle and organic-rich lithofacies. Another two shale lithofacies, laminated mixed mudstone (LMM) and laminated siliceous mudstone (LSM), have thin or thick laminae with low TOC content (Avg 1.45, 2.69%). Argillaceous mudstone (AM) contains the highest clay percent with avg 1.94% TOC content. Calcareous mudstone(CM) has relatively carbonate-rich lithofacies along the study interval and an average of 4.42% TOC content .

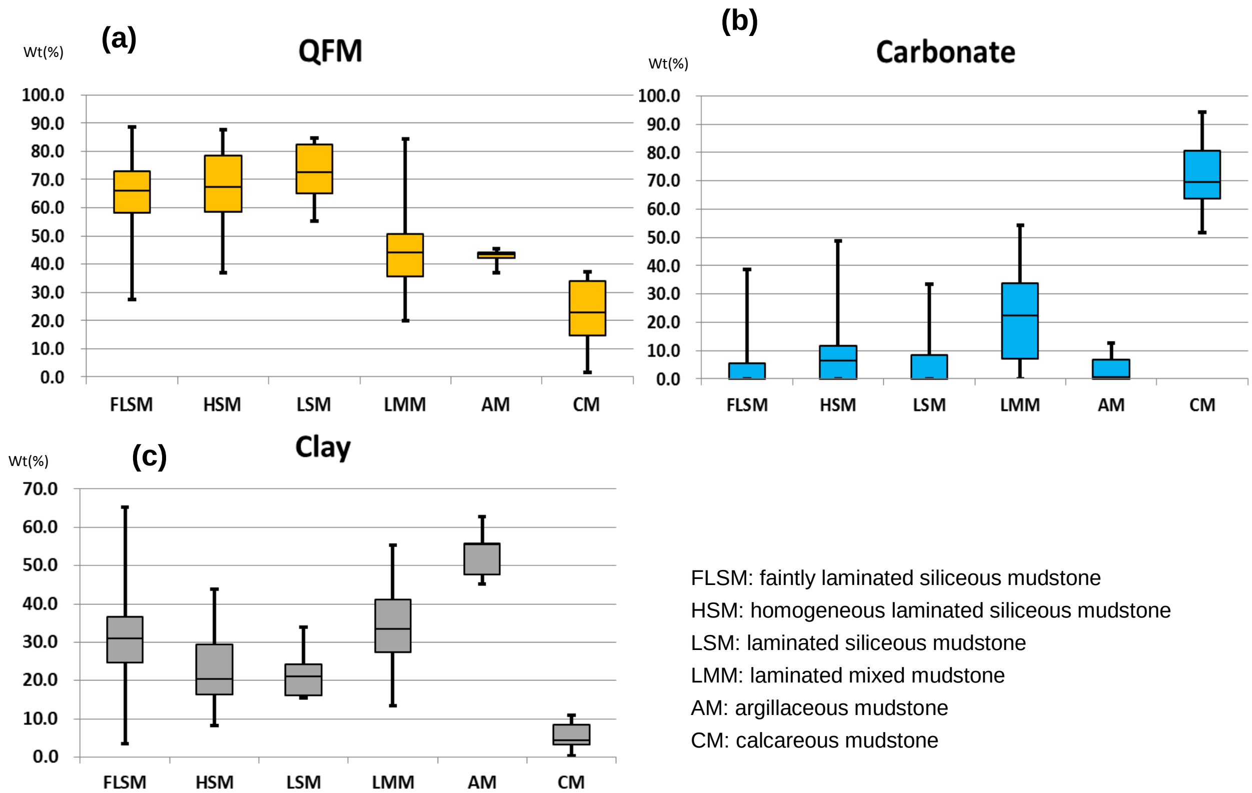

Figure 1. Relative proportions of minerals derived from ECS logs for (**a)** QFM (quartz, feldspar and mica),(**b)** carbonate and (**c)** clay percent of each shale lithofacies.

Electrofacies from conventional logs with core lithofacies

The lithofacies are correlated with wireline log data, including GR, RHOB, NPHI, DT and PE logs (Fig. 2) used to construct an electrofacies model of Horn River shales. This study applied Multi Resolution Graph-Based Clustering (MRGC) algorithm in three wells. MRGC workflow is performed using the Facimage module of Paradigm Geolog software ver. 2015. In order to get high resolution electrofacies classifications, different parameters are applied and select the parameter for best accuracy.

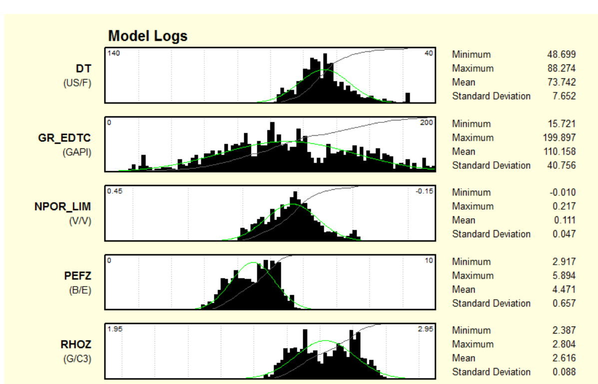

Figure 2. Representing of statistical features five conventional welllog data.

According to the trends in distribution of wireline data, facies FLSM and HSM shows similar distribution pattern, especially gamma ray logs are distributed in the high values. On the other hand, laminated facies LSM, LMM show in the low values of gamma ray and density (Fig. 3).

Facies	weight	DT	GR	NPHI	PE	RHOZ
FLSM	187					
HSM	170					
LSM	88					
LMM	493					
AM	53					
CM	22					

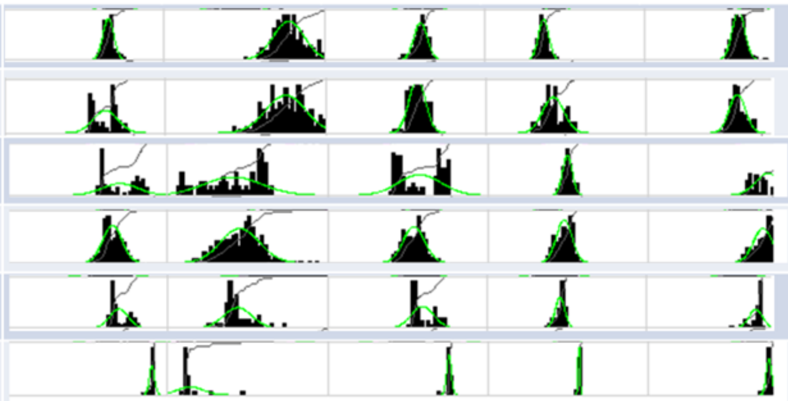

Figure 3. Association of electrofacies units and the distribution of wireline logs represents as histograms. DT= sonic, GR= gamma ray, NPHI= neutron, PE= photo electronic factor, RHOZ= bulk density log.

The MRGC is constructing the three models constrained for each member with trained core-driven lithofacies and then applied non-cored well. Figure 4 Shown the electrofacies of three wells applied to MRGC algorithm. We can find the subtle variation of facies change at each member.

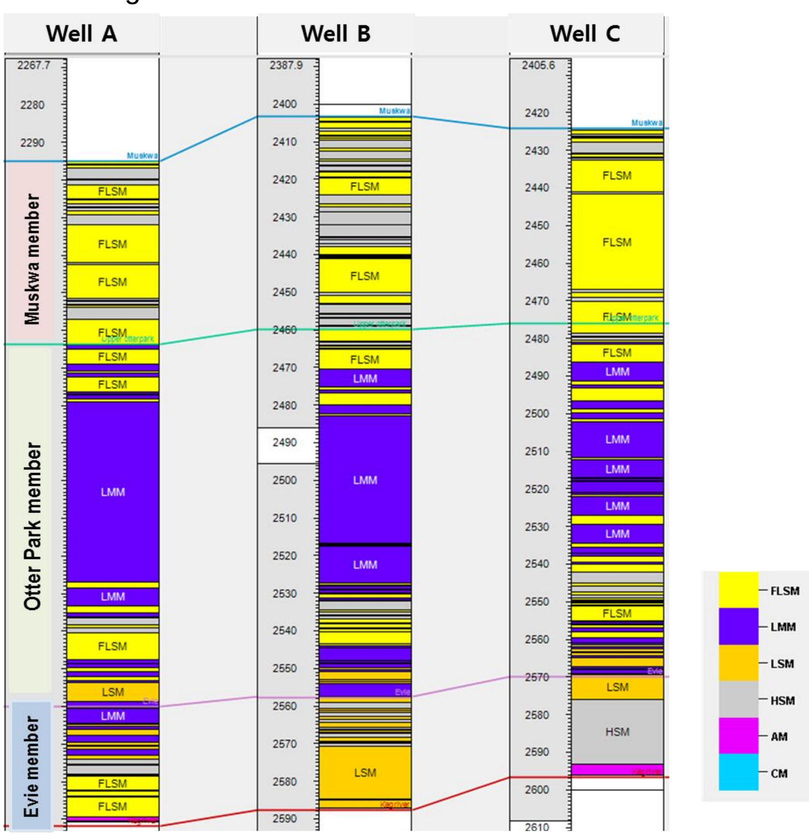

Figure 4. Predicted electrofacies of three wells withMRGC algorithm applied.

Conclusions

MRGC is appropriate method for unsupervised data classification. We build the supervised model for each member in cored well A and then applied non cored well B and C. Suitable parameter selection for MRGC provides higher accuracy between core-facies and electrofacies. The MRGC algorithm has advantages over other approaches when data is limited. Such a method can be used as reference for the study of new wells in the field. The electrofacies constitution enables definition of the depositional environment directly from well logs.

Acknowledgements

This work was supported by the Korea Institute of Energy Technology Evaluation and Planning(KETEP) and the Ministry of Trade, Industry & Energy(MOTIE) of the Republic of Korea (No. 20178510030880).

References

Avanzini, A., Balossino, P., Brignoli, M., Spelta, E., & Tarchiani, C. (2016). Lithologic and geomechanical facies classification for sweet spot identification in gas shale reservoir. *Interpretation, 4*(3), SL21-SL31.

Jarvie, D. M., Hill, R. J., Ruble, T. E., & Pollastro, R. M. (2007). Unconventional shale-gas systems: The Mississippian Barnett Shale of north-central Texas as one model for thermogenic shale-gas assessment. *AAPG Bulletin, 91*(4), 475-499.

Kadhim, F., Samsuri, A., & Alwan, H. (2015). Determination of Lithology, Porosity and Water Saturation for Mishrif Carbonate Formation. *World Academy of Science, Engineering and Technology, International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering, 9*(8), 1025-1031.

Ye, S.-J., & Rabiller, P. (2000). *A new tool for electro-facies analysis: multi-resolution graph-based clustering.* Paper presented at the SPWLA 41st annual logging symposium