Well Log Analysis for Lithology Identification Using Self-Organizing Map (SOM)

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Abstract
This paper employed unsupervised neural network and fuzzy inference system to identify the lithology o f a well log data obtained from the Niger-Delta region of Nigeria. Sixteen fuzzy rules was proposed based on the output of the SOM clustering. The results obtained were analyzed.

(Keywords: Well log, unsupervised neural network, Self-Organizing Map (SOM), lithology, fuzzy inferenc e rules)

1 Introduction.

Analyzing well log data is a major task in the oil industries and it can be time consuming. Over the years, geologists and geoscientists have worked tirelessly to minimize production cost of acquiring these data. Analyses of key parameters such as reservoir permeability using data from petrophysical logging method s are useful and cost-effective in terms of cost, and time to assess the production potential of oil and gas reservoirs (Perez et al., 2005). Of recent, neural networks have emerged as powerful tools to model co mplex systems. The neural network analysis method enables the estimation of permeability and porosity using various algorithms with sparse analog data as input. Since in neural networks the data analysis are carried out in parallel and distributed method, their ability to recognize complex relationships between multiple variables can be presented to the neural network. It is on this premise that this research is gear ed towards analyzing well log data obtained from the Niger delta region of Nigeria using unsupervised n eural network and fuzzy inference system to determine the lithology and fluid content of the data given. A neural network is an artificial representation of the human brain that tries to simulate its learning proc ess. (Chakraborty, 2010). Recently, the use of neural network in geophysical interpretation evolved. The non-uniqueness of the geophysical inverse problem, as pointed out by Backus and Gilbert (1968) results from the impossibility of obtaining from a finite number of observations, the continuous spatial distribut ion of the physical property (or the mineralogical composition in the case of well logging). Uniqueness of the geophysical interpretation is usually attained either by reducing the information demand about the sources to a level dictated by the effective amount of information contained in the geophysical data (Ba ckus and Gilbert, 1968), or by incorporating a priori information about the real, sources (Tikhonov, 1963) . However, the introduction of a priori information necessary to guarantee the uniqueness does not impl y stability in the presence of noise. The degree of stability will depend on the quality and quantity of the priori information introduced.

The knowledge of the lithology of an oil well can be used to determine several characteristics. The conv entional method used for the identification of lithofacies is by direct observation of underground cores (Chang et al., 2002). Lithology determination by direct observation of underground cores is an expensive process, time consuming and is not always reliable and valid because different geologists may provide di fferent interpretations.
Well logging also provides in situ and continuous data, as well as yielding a number of economic benefits by saving the cost and time of core analyses.

1.1 Geology of the Niger Delta

The study area is located within the Niger Delta, Nigeria. The Niger Delta sedimentary basin is a product of triple junction phenomenon comprising the Gulf of Guinea, South Atlantic Ocean and Benue depressi on.

The geology of the Tertiary section of the Niger Delta is divided into three formations, representing dep ositional facies distinguished mostly on the basis of sand-shale ratio [Kulke,1995]. They are namely Beni n Formation, the Agbada Formation and Akata Formation. They range in age from Paleocene to Recent. The Benin Formation is a continental latest Eocene to recent deposit of alluvial and upper coastal plain s ands. It consists predominantly of freshwater baring massive continental sands and gravels deposited in an upper deltaic plain environment. The Agbada Formation which consists of paralic Siliciclastics underli es the Benin Formation. The Agbada Formation consists of fluvio-marine sands, siltstones and shales. Th e sandy parts constitute the main hydrocarbon reservoirs. The grain sizes of these reservoirs range from very coarse to fine. The Niger Delta province is generally adjudged to contain only one identified petrole um system referred to as the tertiary Niger delta (Akata-Agbada) petroleum system [Michele et al, 1999] . The Agbada Formation is of marine origin and composed of thick shale sequences (potential source roc k), turbidites sand (potential reservoirs in deep water and minor amount of clay and silt. Beginning in th e Paleocene and through the Recent, the Akata Formation formed during low stands, when terrestrial or ganic matter and clays were transported to deep-sea water areas characterized by low energy condition s and oxygen deficiency [Stacher, 1995]. It is the major source rock in the Niger Delta.

1.2 Data collection

The well data used in this study consist of gamma ray, Deep resistivity, Density and Neutron logs which was made available by Shell Producing Development Company, Nigeria.

1.3 self-Organizing Map Clustering

Basically, there are two types of neural network; the supervised neural network and the unsupervised n eural network. This research made use of the unsupervised neural network in analyzing the well log data .

The unsupervised neural network is also known as the Self- organizing map (SOM). The self-organizing map [Kohonen, 1995] is especially suitable for data survey because it has prominent visualization proper ties. It creates a set of prototype vectors representing the data set and carries out a topology preserving projection of the prototypes from the d-dimensional input space onto a low-dimensional grid. This order ed grid can be used as a convenient visualization surface for showing different features of the SOM (and thus of the data), for example, the cluster structure [Vesanto, 1999]. However, the visualizations can onl y be used to obtain qualitative information. To produce summaries—quantitative descriptions of data pr operties—interesting groups of map units must be selected from the SOM.

2 Procedure of analysis

The raw well log data was processed and fed into the Kohonen self-organing map (SOM). The SOM was used to cluster the well data into sixteen cluster units as shown in table 1. A clustering means partitionin g a data set into a set of clusters. The clustering is carried out using a two-level approach, where the dat a set is first clustered using the SOM, and then, the SOM is clustered. The most important benefit of this procedure is that computational load decreases considerably, making it possible to cluster large data set s and to consider several different preprocessing strategies in a limited time. Naturally, the approach is v alid only if the clusters found using the SOM are similar to those of the original data.

Table 1: The cluster well data.

CLUSTERS	**CLUSTER SAMPLE**
1	125
2	66
3	227
4	229
5	291
6	86
7	98
8	143
9	148
10	74
11	157
12	157
13	32
14	94
15	28
16	14

After training the SOM, the network have learned the pattern of the input data. The test data file is sub mitted to the trained SOM network, which then identifies the clusters it had recognized during the traini ng process and the data samples are assigned to cluster groups. An output report typical of the form pre sented in Table 1 is generated.

The computed mean of the log values as shown in table 2, was used to infer the lithology of the well exa mined via fuzzy rules.

Table 2. The computed mean of the clusters.

CLUSTERS	CLUSTER SAMPLE	GR	DEEP-R E	NEU	DEN
1	125	98.446	3.372	0.3859	2.337
2	66	70.584	4.631	0.3056	2.194
3	227	35.910	2.494	0.3052	2.054
4	229	25.394	2.537	0.2985	2.013
5	291	90.109	2.612	0.4219	2.288
6	86	46.687	5.002	0.3092	2.094
7	98	29.797	7.574	0.2808	2.112
8	143	24.197	16.383	0.2608	2.131
9	148	83.471	3.481	0.3488	2.322
10	74	57.941	3.009	0.3068	2.093
11	157	24.871	25.360	0.2602	2.123
12	157	26.540	36.351	0.2602	2.148
13	32	49.664	23.453	0.2962	2.150
14	94	32.425	25.204	0.2719	2.102
15	28	27.723	94.351	0.1182	2.111
16	14	28.154	146.230	0.1528	2.069

Based on the number of clusters, fuzzy inference system is applied to ascertain the lithology of the well. The computed mean of the log values was used to infer the lithology of the rock species that characteriz e the geological formation of the oil well being investigated by determining their fuzzy value.

In determining the fuzzy rules for the well log, we considered the gamma ray log as one of the factors th at determine the sandy or shally nature of the well under consideration. The deep resistivity log was use d to determine the presence of any hydrocarbon. The neutron and density logs were used to ascertain oi l, gas and water bearing regions.

The general fuzzy inference process, the following steps are taken (Krause et al, 1994):

Fuzzification which involves the conversion of numeric data in real world domain to fuzzy numbers in fuz zy domain.

Fuzzy inference which involves the computation of the truth value of each rule and its application to the conclusion part of the rule.

Composition of the output variables of sub rules which can fire in parallel for the purpose of drawing a gl obal conclusion.

Deffuzzification, which is optional, involves the conversion of the derived fuzzy number to the numeric data in real world domain.

The fuzzy inference process started with the fuzzification sub-process where the membership functions defined on the input variables were applied to their actual values to determine the degree of truth for e ach rule premise. If a rules premise has a non-zero degree of truth, then the rule fires. In the inference s ub-process, the truth value of each rule was computed and applied to its conclusion part.

The fuzzy membership functions for each of the logs are presented in the figures below.

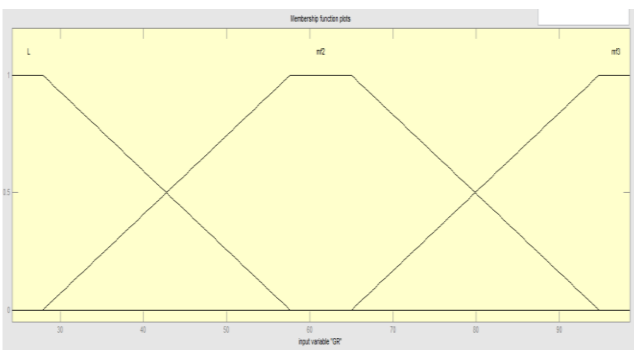

Figure 1: Gamma ray membership function

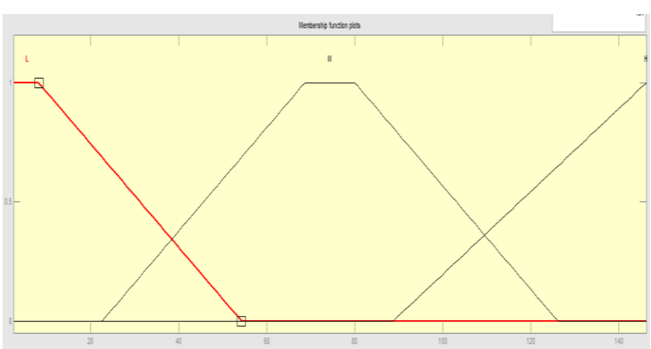

Figure 2: Deep resistivity membership function.

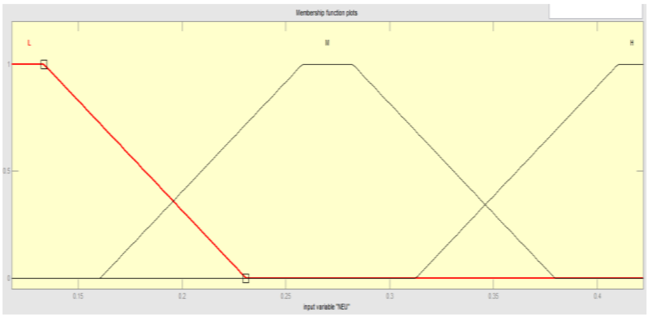

Figure 3: Neutron log membership function.

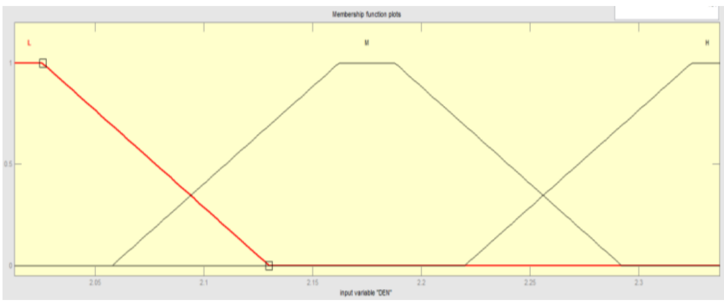

Figure 4: Density log membership function.

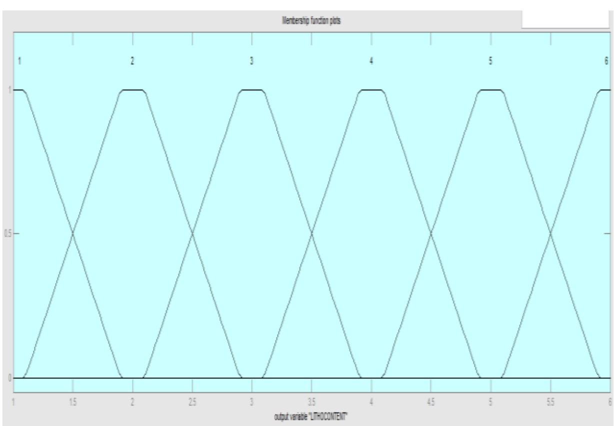

Figure 5: output membership function.

The output representation (1 = sand, 2 = low reservoir quality (LRQ), 3 = shale, 4 = gas, 5 = oil, 6 = water)

The fuzzy rules matrix presented in Table 3 was derived from the SOM cluster output and the characteris tic response of the lithology logs to the logging tools in the rock materials.

The results after carrying out the inference procedure showing the lithology inferred from the cluster gr oups are presented in Table 3.

Table 3 : Fuzzy Inference Output.

cluster	lithology	legend
1	shale	3
2	shale	3
3	water	6
4	water	6
5	shale	3
6	shale	3
7	LRQ	2
8	LRW	2
9	shale	3
10	shale	3
11	LRQ	2
12	oil	5
13	LRQ	2
14	shale	3
15	oil	5
16	gas	4

From table 3, it can be infer that clusters 1, 2, 5, 6, 9, 10 and 14 represent shales. Clusters 3 and 4 repres ent water bearing region. Clusters7, 8, 11 and 13 represent region of low reservoir quality (LRQ). Cluster s 12 and 15 represent a hydrocarbon reservoir. Cluster 16 represent gaseous region. The results were ve rified by a geophysicist and a geologist who are quite familiar with the data employed.

The appendix shows the well log examined and the SOM clustering of the well.

2.1 Conclusion

This paper presented unsupervised neural network (SOM) as used to cluster well log data obtained from the Niger-Delta region of Nigeria. The fuzzy inference method used in the interpretation of the clusters was based on the conventional way of log interpretation. The general lithology of the Niger-Delta is mai nly shale and sand. The result obtained in this work is in agreement with the lithology of the studied are a. The SOM based clustering and fuzzy inference rules used in this paper can be adopted as a basis for th e development of a neural network and fuzzy expert systems that can be used in detecting the nature of the sub-surface in an oil field.

Reference

Backus, G. E., and Gilbert, F., (1968): The resolving power of gross earth data: Geophys. J. Roy. Astr. Soc., 16, 169-205.

Chakraborty R. C. (2010): fundamentals of Neural Networks; AI Cousre lecture 37-38, notes, slides.

Chang, H., Kopaska-Merkel, D. and Chen.(2002). "Identification of Lithofacies using Kohonen Self-Organi zing Maps". *Computers and Geosciences*. 28: 223 – 229.

Kohonen T., (1995) *Self-Organizing Maps*. Berlin/Heidelberg, Germany: Springer, vol. 30.

Krause, R., Gebhardt, J., and Klawonn, F. (1994). *Foundations of Fuzzy Systems*. John Wiley and Sons: New York, NY. ISBN 04719422243X. pp265.

Kulke H., (1999) "Nigeria," In: H., Kulke, Ed., Regional Petroleum Geology of the World Part, 11, Gebrude r Michele L. W. T., R. C. Ronald and E. B. Michael, "The Niger Delta Petroleum System: Niger Delta Provin ce, Nigeria, Cameroon, and Equatorial Guinea, Africa," Open-File Report 99-50-H, United States Geol ogical Survey,

Stacher P., (1995) "Present Understanding of the Niger Delta Hydrocarbon Habitat," In: M. N. Oti and G.

Perez H.H., Gupta A.D., Mishra S., (2005). The role of electrofacies, lithofacies, and hydraulic flow units i n permeability prediction from well logs: A comparative analysis using classification trees. SPE Reservoir Evaluation and Engineering.

Postma, Eds., Geology of Deltas, FRotterdam A. A, Bakkema, pp. 57-267.

Tikhonov, A. N., (1963) The solution of ill-posed problems: Doklady Akad. Nauk SSSR, 151, 501-504.

Vesanto J., (1999) "SOM-based data visualization methods," *Intell. Data Anal.*, vol. 3, no. 2, pp. 111–126,