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Application of Multivariate Membership Function Discrimination Method for Lithology Identification

(Aplikasi Kaedah Diskriminasi Fungsi Keahlian Multivariat untuk Pengenalan Litologi)

JUN ZHAO*, FEIFEI WANG & YIFAN LU

ABSTRACT

Formation lithology identification is an indispensable link in oil and gas exploration. Precision of the traditional recognition method is difficult to guarantee when trying to identify lithology of particular formation with strong heterogeneity and complex structure. In order to remove this defect, multivariate membership function discrimination method is proposed, which regard to lithology identification as a linear model in the fuzzy domain and obtain aimed result with the multivariate membership function established. It is indicated by the test on lower carboniferous Bachu group bioclastic limestone section and Donghe sandstone section reservoir on T Field H area that satisfactory accuracy can be achieved in both clastic rock and carbonate formation and obvious advantages are unfold when dealing with complex formations, which shows a good application prospect and provides a new thought to solve complex problems on oilfield exploration and development with fuzzy theory.

Keywords: Fuzzy theory; lithology identification; logging interpretation; multivariate membership function

ABSTRAK

Pengenalan kepada formasi litologi adalah pautan yang amat diperlukan dalam penerokaan minyak dan gas. Ketepatan pengiktirafan kaedah tradisi adalah sukar dijamin apabila cuba untuk mengenal pasti formasi litologi untuk formasi tertentu dengan keheterogenan yang tinggi serta struktur yang kompleks. Untuk menghapuskan kesilapan ini, kaedah diskriminasi fungsi keahlian multivariat dicadangkan, dengan pengenalan litologi sebagai model linear dalam domain kabur dan mendapat keputusan yang diinginkan dengan penubuhan fungsi keahlian multivariat. Ini ditunjukkan dengan ujian ke atas Karbon Rendah kumpulan Bachu seksyen Bioclastic batu kapur dan seksyen takungan batu pasir Donghe pada lapangan T kawasan H bahawa ketepatan memuaskan boleh dicapai pada kedua-dua batu klastik dan formasi karbonat serta kelebihan yang ketara terungkap apabila berurusan dengan formasi yang kompleks, justeru menunjukkan prospek aplikasi yang baik dan memberikan cara baru untuk menyelesaikan masalah yang kompleks dalam bidang penerokaan lapangan minyak dan pembangunan dengan teori kabur.

Kata kunci: Fungsi keahlian multivariat; pengelogan tafsiran; pengenalan litologi; teori kabur

INTRODUCTION

Formation lithology identification is the foundation of reservoir evaluation and modeling as well as a crucial link of well logging interpretation, which shows great value for oilfield production. With the continues improvement of engineering technology and expansion of petroleum demand, the development and exploration of complex reservoirs, which shows strong heterogeneity and multifaceted lithology due to its distinctive sedimentary environments and geotectonic conditions, gradually draws the attention of many geologists. Traditional measures (Bateman 1977; Jalal et al. 2017) with cross plots or overlapped logging curves rely too much on human judgment that the current results are not always obtained. Moreover, couple defects remain insurmountable on the judgment of characteristic parameter proportion and training rate for commonly used algorithms, such as fisher discrimination (Zhang et al. 2008), KNN (Houston 1992; Huang & Yuan 1995), neural network (Huang & Yuan 1995) and decision tree (Mudford 2000) and other multivariate analysis and data mining approaches, which makes the obtainment of satisfactory results pretty difficult when dealing with the problems with multiple parameters and large data.

MMFD, short for Multivariate Membership Function Discrimination Method, based on fuzzy logic and fuzzy probability theory (Hambalek & Gonzalez 2003; Imamura 1994), sees the problem of lithology identification as a linear combination model of multiple discriminant factors in order to select parameters and build multivariate membership function with the least square method and determine the thresholds according to maximum membership degree law (Xu et al. 2006; You & Rahim 2017). In this case, the samples can be identified as expected.

Materials and Methods

Formation lithology can be synthetically characterized by plenty of logging factors. However, for some complex formations, no specific indexes can be found to separate different lithology directly. Then these identification problems can be classified as typical fuzzy problems.

Define the study formation area as U, the fuzzy domain. On the basis of the analysis of core observation and mud logging data, lithologies can be roughly classified into m categories, as our aimed lithology categories, marked as $A_1, A_2, \cdots, A_m$.

From the samples that their lithologies are determined, select n_1, $n_2 \cdots$ n_m samples respectively for each lithology to build a learning sample set. Then a fuzzy subset with the sample size of n ($n = n_1 + n_2 + \cdots + n_m$) can be formed:

$$\tilde{A} = \{A_1, A_2, \cdots, A_m\}, \tag{1}$$

and induct those unrecognized samples into an undetermined sample set.

Choose p parameters or its derivatives that can appropriately characterize these lithologies as discrimination factors. Then each sample in this set can be expressed with p vectors:

$$u_i = \left(x_{i1}, x_{i2}, \cdots, x_{ip}\right) \ (i = 1, 2, \cdots, n), \tag{2}$$

where, $x_{i1}, x_{i2}, \cdots, x_{ip}$ are the p discrimination factors value of the i sample.

There is one thing we should take into consideration that conventional parameters used on logging interpretation, generally GR, SP, RD, RS, AC, DEN, CNL, U, TH, K and their derivatives, always span one or more orders of magnitude that standardization is required before operation to remove errors cause by dimensional difference.

Each lithology can be considered as the linear combination of p discrimination factors:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_i x_{ip} + \varepsilon_i \quad (i = 1, 2, \cdots, n), \tag{3}$$

where, ε_i is a normal random variable which meets the condition of $E(\varepsilon_i) = 0$ and $D(\varepsilon_i) = \sigma^2$, in which $i = 1, 2, \cdots, n$ and σ is a constant.

It can also be expressed as a matrix:

$$\underset{n\times 1}{Y} = \underset{n\times(p+1)}{X} \cdot \underset{(p+1)\times 1}{\mathrm{B}} + \underset{n\times 1}{\mathrm{E}}, \tag{4}$$

where Y is matrix of lithology categories; X is matrix of learning samples; B is matrix of undetermined parameters; E is matrix of errors (Rabben & Ursin 2007; Zhang et al. 2012; Zhou et al. 2016).

Do map f from U to set $\tilde{A} = \{A_1, A_2 \cdots A_m\}$

$$f(u_i) = \begin{cases} 1, & u_i \in A_1 \\ 1/2, & u_i \in A_2 \\ \cdots & \\ 1/m, & u_i \in A_m \end{cases}. \tag{5}$$

Then the matrix of lithology categories can be described as

$$Y = (\underbrace{1, \cdots, 1}_{n_1}, \underbrace{1/2, \cdots, 1/2}_{n_2}, \cdots, \underbrace{1/m, \cdots, 1/m}_{n_m})^T, \tag{6}$$

while the matrix of learning samples can be described as

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1p} \\ 1 & x_{21} & x_{22} & \cdots & x_{2p} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}, \tag{7}$$

where x_{ij} stands for the j discrimination factor of i sample.

Obviously, the other two matrixes left in linear function (4), B and E, can also be described as

$$\mathrm{B} = \left(\beta_0, \beta_1, \beta_2, \cdots, \beta_p\right)^T. \tag{8}$$

$$\mathrm{E} = \left(\varepsilon_0, \varepsilon_1, \varepsilon_2, \cdots, \varepsilon_p\right)^T. \tag{9}$$

As it is our aim to make the predict results as realistic as possible, an error that is small enough is needed, which means we require to calculate a linear function with minimal $E^T E$. In most cases for lithology identification, sample size n and the quantity of discriminant factors p fulfill the condition of $n \gg p$. At this time, this problem is equal to compute the minimum value of $\mathrm{E} = Y - X \cdot \mathrm{B}$, i.e. to obtain the generalized solution of over determined equation, $Y = X \cdot \mathrm{B}$.

According to least square theory, the solution as well as the least squares estimation of B becomes

$$\tilde{\mathrm{B}} = \left(\tilde{\beta}_0, \tilde{\beta}_1, \tilde{\beta}_2, \cdots, \tilde{\beta}_p\right)^T = \begin{cases} \left(X^T X\right)^{-1} X^T Y, \mathit{if}\ \mathrm{rank}\left(X^T X\right) = p+1 \\ \left(X^T X\right)^{+} X^T Y, \mathit{if}\ \mathrm{rank}\left(X^T X\right) < p+1 \end{cases}, \tag{10}$$

where, matrix with superscript "-1" means inverse matrix while it with "+" stands for Moore-Penrose generalized inverse matrix.

Due to the intricate geological environment and unorganized data points, samples tend to be non-linear. Take the above into account, a non-linear multivariate membership function could be created in the form of Logistic function as

$$A(u)=\frac{1}{1+\exp\left[\alpha\left(\tilde{\beta}_0+\sum_{i=1}^{p}\tilde{\beta}_i x_i\right)\right]}, \tag{11}$$

where α is a consist whose value should be determined based on professional knowledge or practical experience. For most engineering problem, include this one, consider α as -3 in order to simplify the calculation. Also, you can achieve a more accurate value with a great deal of test and validation, which is believed not that necessary for the precision of final result.

Substitute $\tilde{\mathrm{B}}$ and learning samples into (11), with matrix Y associated, the value ranges that these m kind of lithologies corresponding to become available, from which a vector of thresholds that can clearly separate the learning sample set into m categories is concluded:

$$\Lambda=\{\lambda_1,\lambda_2,\cdots,\lambda_{m\text{-}1}\}, \tag{12}$$

where thresholds fulfill the condition that $\lambda_j\in[0,1]$ and $\lambda_j>\lambda_{j+1}\ (j=1,2,\cdots,m-1)$.

Substitute undetermined samples into (9) and for each sample a $A(u)$ value is obtained. Thus the undetermined sample set can be divided into m subsets, denoted as $A_1^*,\ A_2^*\cdots\ A_m^*$, referring to the thresholds in (12):

$$\begin{cases}A_1^*=\{u_i^*\,|\,A(u_i^*)\ge\lambda_1\}\\ A_2^*=\{u_i^*\,|\,\lambda_2\le A(u_i^*)<\lambda_1\}\\ \cdots\\ A_m^*=\{u_i^*\,|\,A(u_i^*)<\lambda_{m-1}\}\end{cases}, \tag{13}$$

Then the lithology of each sample will be in accordance with the subset it belongs.

Results

In order to verify its practicability, this approach got tested on Lower Carboniferous Bachu Group both Donghe Sandstone Section and Bioclastic Limestone Section reservoirs of 24 wells in T oilfield H area.

Donghe Sandstone Section

The whole Donghe Sandstone Section is regarded as domain U and the stratum is summarized into four lithologies - mudstone, fine sandstone, medium sandstone and conglomerate, denoted as subset $\tilde{A}=\{A_1,\ A_2\ \ A_3\ \ A_4\}$. Six conventional well logging parameters - GR, RD, RS, AC, DEN and CNL - are chosen as discriminant factors. 21 mudstone samples, 25 fine sandstone samples, 31 medium sandstone samples and 14 conglomerate samples that are typical and classic are extracted as learning sample set and get it standardized.

Mapping f is done from U to $\tilde{A}$

$$f(u_i)=\begin{cases}1\ ,\ \textit{if}\ u_i\ \textit{is mudstone}\\ 1/2,\ \textit{if}\ u_i\ \textit{is fine sandstone}\\ 1/3,\ \textit{if}\ u_i\ \textit{is medium sandstone}\\ 1/4,\ \textit{if}\ u_i\ \textit{is conglomerate}\end{cases}. \tag{14}$$

Thus for linear model $Y=X\cdot\mathrm{B}+\mathrm{E}$, the matrix of lithology categories is

$$Y=(\underbrace{1,\cdots 1}_{21}\ \underbrace{1/2\ \cdots\ 1/2}_{25}\ \underbrace{1/3\ \cdots\ 1/3}_{31}\ \underbrace{1/4\ \cdots\ 1/4}_{14})^T\ . \tag{15}$$

Make α equal to -3. The multivariate membership function is created as

$$A(u)=\frac{1}{1+\exp\left[-3\left(\tilde{\beta}_0+\sum_{i=1}^{p}\tilde{\beta}_i x_i\right)\right]}. \tag{16}$$

After calculation, three thresholds - 0.9, 0.79 and 0.72 - are determined to identify unrecognized samples. Then for a casual sample u_i^*

$$\begin{cases}\textit{If}\ A(u_i^*)\ge 0.9\ ,\ u_i^*\ \textit{will be identified as mudstone}\\ \textit{If}\ 0.79\le A(u_i^*)<0.9\ ,\ u_i^*\ \textit{will be identified as fine sandstone}\\ \textit{If}\ 0.72\le A(u_i^*)<0.79\ ,\ u_i^*\ \textit{will be identified as medium sandstone}\\ \textit{If}\ A(u_i^*)<0.72\ ,\ u_i^*\ \textit{will be identified as conglomerate}\end{cases}. \tag{17}$$

From the thin section analysis results, 40 samples are extracted casually to establish an undetermined sample set. Test on it claims that MMFD has a identification accuracy of 92.5% (Table 1).

Using MMFD on all wells in this area and take well M4 as example to explain its practicability. As is shown in geologic stratification and mudlogging data, the depth interval from 1987 to 2015 meters is affirmed as Donghe Sandstone Section, in which stratum from 1987 to 1989 m is fine sandstone, 1989 to 1992.5 m mudstone, 1992.5 to 2008 m medium sandstone and 2008 to 2015 m conglomerate. The identification result dovetailed nicely with cutting logging result which proves this approach is able to attain a satisfactory effect when dealing with lithology identification problems in clastic rock reservoirs (Figure 1).

TABLE 1. Test result of MMFD algorithm on Donghe Sandstone Reservoir

NO	GR API	RD Ω·m	RS Ω·m	AC μs/ft	DEN g/cm³	CNL %	A(u)	Thin Section Analysis Results	MMFD Results
1	22.571	52.562	76.842	58.095	2.662	4.21	0.765	C	C
2	33.644	51.028	66.136	58.373	2.663	5.52	0.869	B	B
3	101.00	33.475	42.798	64.388	2.715	11.33	0.874	B	B
4	44.027	98.206	114.11	53.777	2.744	1.44	0.708	D	D
5	6.632	642.84	590.25	48.421	2.736	10.21	0.799	B	B
6	6.862	1006.9	824.01	48.023	2.731	9.12	0.860	B	B
7	32.477	47.311	41.667	71.665	2.682	5.15	0.745	C	C
8	44.914	76.286	70.683	60.892	2.667	2.89	0.788	C	C
9	64.971	41.018	41.154	65.865	2.611	6.05	0.757	C	C
10	49.354	29.309	29.634	67.927	2.699	9.14	0.740	C	C
11	35.485	243.74	218.89	56.995	2.725	1.67	0.741	C	C
12	38.166	264.42	229.23	54.682	2.723	1.62	0.751	C	C
13	38.933	59.542	49.235	63.251	2.627	3.57	0.769	C	C
14	27.624	61.796	54.844	65.511	2.622	5.41	0.784	C	C
15	65.482	51.863	41.031	61.438	2.711	4.93	0.751	C	C
16	46.985	75.346	57.549	56.492	2.572	4.56	0.810	B	B
17	41.595	51.233	38.621	60.191	2.204	8.04	0.744	C	C
18	42.334	48.468	36.066	61.121	2.304	8.05	0.727	C	C
19	36.322	61.729	42.899	61.379	2.718	6.28	0.874	B	B
20	36.191	102.34	83.081	57.594	2.712	4.54	0.727	D	C
21	37.735	170.94	150.82	55.292	2.686	3.43	0.890	B	B
22	30.613	49.733	46.124	58.553	1.843	4.47	0.870	B	B
23	38.375	56.668	35.954	72.796	2.612	1.21	0.643	D	D
24	11.307	276.52	206.91	58.469	2.645	0.93	0.716	D	D
25	27.346	128.38	102.54	57.793	2.719	1.47	0.644	D	D
26	27.371	118.22	94.726	57.729	2.722	1.44	0.703	D	D
27	121.07	40.012	33.609	61.136	2.577	2.97	0.942	D	A
28	103.34	17.698	14.715	63.402	2.561	10.89	0.758	D	C
29	51.008	63.586	79.473	61.777	2.779	14.54	0.821	B	B
30	34.225	123.02	149.15	57.321	2.754	8.55	0.872	B	B
31	64.991	89.632	107.02	59.877	2.726	3.88	0.789	C	C
32	37.361	138.18	153.35	56.655	2.762	6.80	0.878	B	B
33	37.096	139.25	154.87	54.564	2.741	3.24	0.868	B	B
34	27.223	107.89	74.989	66.905	2.614	2.25	0.730	C	C
35	23.953	215.89	150.84	68.343	2.664	0.87	0.621	D	D
36	56.205	146.88	107.05	63.329	2.679	1.69	0.667	D	D
37	22.571	52.562	76.842	58.095	2.667	4.26	0.865	B	B
38	33.644	51.028	66.136	58.375	2.663	5.57	0.869	B	B
39	101.00	33.475	42.798	64.388	2.715	11.32	0.763	C	C
40	44.027	98.206	114.11	53.777	2.744	1.41	0.808	B	B

A, mudstone; B ,sandstone; C, medium sandstone; and D conglomerate

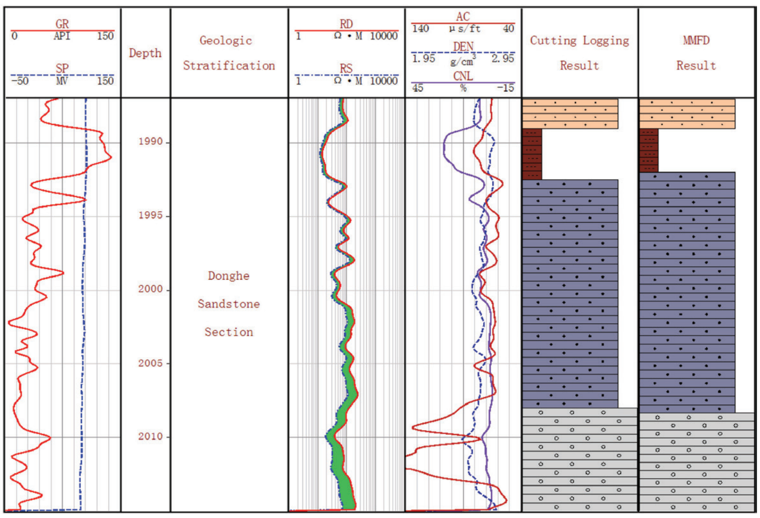

FIGURE 1. Lithology identification result on Well M4

Bioclastic limestone section

The whole Bioclastic Limestone Section is regarded as domain U and the stratum is summarized into four lithologies - bioclastic limestone, calcirudite, micrite and dolomite, denoted as subset $\tilde{A} = \{A_1, A_2 \ A_3 \ A_4\}$. Six conventional well logging parameters - GR, RD, RS, AC, DEN and CNL - are chosen as discriminant factors. 41 bioclastic limestone samples, 17 calcirudite samples, 38 micrite samples and 28 dolomite samples are extracted as learning sample set and get it standardized.

Mapping f is done from U to $\tilde{A}$

$$f(u_i) = \begin{cases} 1 \ , \ if \ u_i \ is \ bioclastic \ limestone \\ 1/2, \ if \ u_i \ is \ calcirudite \\ 1/3, \ if \ u_i \ is \ micrite \\ 1/4, \ if \ u_i \ is \ dolomite \end{cases} \quad (18)$$

Processing the same steps and there thresholds - 0.86, 0.77 and 0.7 - are determined to identify unrecognized samples. Then for a casual sample

$$\begin{cases} If \ A(u_i^*) \geq 0.86 \ , \ u_i^* \ will \ be \ identified \ as \ bioclastic \ limestone \\ If \ 0.77 \ \leq A(u_i^*) < 0.86 \ , \ u_i^* \ will \ be \ identified \ as \ calcirudite \\ If \ 0.7 \ \leq A(u_i^*) < 0.77 \ , \ u_i^* \ will \ be \ identified \ as \ micrite \\ If \ A(u_i^*) < 0.7 \ , \ u_i^* \ will \ be \ identified \ as \ dolomite \end{cases} \quad (19)$$

From the thin section analysis results, 40 samples were extracted casually to establish an undetermined sample set. Test on it claims that MMFD has a identification accuracy of 85% (Table 2).

TABLE 2. Test result of MMFD algorithm on bioclastic limestone reservoir

NO	GR API	RD Ω·m	RS Ω·m	AC μs/ft	DEN g/cm³	CNL %	A(u)	Thin section analysis results	MMFD results
1	14.223	267.82	274.82	50.823	2.725	1.232	0.711	C	C
2	15.261	172.37	171.87	50.948	2.742	1.696	0.701	C	C
3	17.385	48.927	54.872	55.043	2.599	7.738	0.646	D	D
4	12.987	157.95	144.94	52.748	2.784	3.072	0.633	D	D
5	14.712	122.95	115.43	51.791	2.739	4.095	0.573	D	D
6	15.035	229.47	250.11	50.869	2.759	1.955	0.637	D	D
7	14.156	164.71	182.98	51.974	2.716	1.883	0.650	D	D
8	19.088	62.604	71.711	53.429	2.675	6.108	0.642	D	D
9	18.742	45.274	51.524	54.636	2.524	9.179	0.662	D	D
10	17.925	72.187	82.097	54.681	2.656	5.079	0.849	B	B
11	16.085	121.55	137.70	53.343	2.633	3.043	0.869	A	A
12	15.125	142.95	110.43	51.714	2.737	3.992	0.740	C	C
13	27.524	94.855	14.694	52.787	2.436	19.20	0.570	C	D
14	26.221	84.237	12.963	52.929	2.404	27.06	0.551	C	D
15	13.743	82.552	16.645	67.012	1.711	35.31	0.768	C	C
16	17.266	67.619	12.975	62.124	2.386	27.51	0.585	C	C
17	22.271	67.094	43.025	90.459	2.575	13.32	0.700	C	C
18	20.176	168.54	157.45	61.167	2.507	3.004	0.840	C	B
19	50.971	12.389	11.406	106.29	2.318	35.70	0.784	B	B
20	38.974	69.216	78.156	57.613	2.682	4.319	0.775	B	B
21	24.403	160.33	138.04	53.826	2.697	1.749	0.773	B	B
22	28.519	102.47	117.31	56.457	2.709	3.962	0.863	A	A
23	19.277	195.27	204.97	53.111	2.703	1.356	0.871	A	A
24	21.079	96.317	96.584	54.632	2.734	4.783	0.607	D	D
25	7.735	240.83	207.30	50.136	2.739	2.841	0.653	D	D
26	42.997	94.777	102.45	54.347	2.702	3.753	0.846	B	B
27	11.878	155.13	156.32	49.544	2.619	5.024	0.823	C	B
28	15.405	89.506	96.479	52.308	2.752	3.238	0.719	C	C
29	16.759	111.77	119.42	55.877	2.701	4.429	0.626	D	D
30	29.821	64.515	66.183	58.134	2.662	6.134	0.743	C	C
31	10.872	52.013	43.112	53.752	2.742	8.001	0.742	C	C
32	14.695	60.934	61.984	52.276	2.741	5.928	0.895	A	A
33	22.293	94.512	111.51	53.965	2.709	4.436	0.868	A	A
34	31.251	61.971	64.951	55.986	2.707	5.013	0.874	A	A
35	26.629	109.88	144.78	52.687	2.687	2.508	0.906	A	A
36	19.491	200.72	264.50	51.882	2.688	2.046	0.930	A	A
37	24.997	35.166	30.435	58.183	2.642	7.175	0.924	A	A
38	22.079	86.314	86.854	51.362	2.743	4.773	0.807	D	B
39	33.464	139.97	167.36	53.686	2.766	3.656	0.830	B	B
40	23.076	210.67	273.05	51.706	2.749	1.529	0.924	B	A

A, bioclastic limestone; B calcirudite; C micrite; and D dolomite

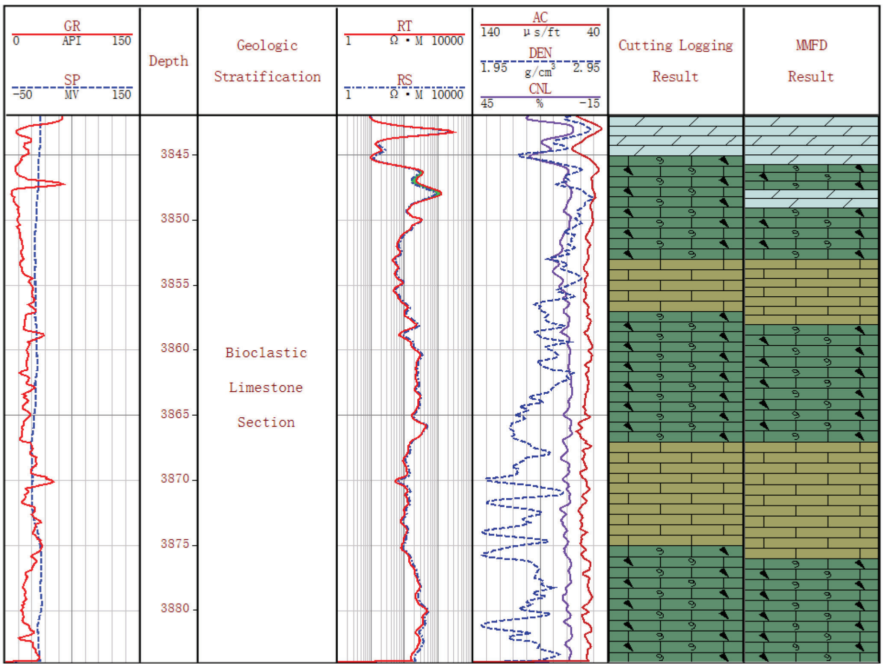

FIGURE 2. Lithology identification result on Well M10

Using MMFD on all wells in this area and take well M10 as example to explain its practicability. As is shown in geologic stratification and mudlogging data, the depth interval from 3842 to 3885 m is affirmed as Bioclastic Limestone Section, in which stratum 3842-3845 m is dolomite, 3845-3853, 3857-3867 and 3875-3885 m bioclastic limestone and 3853-3857 and 3867-3875 m micrite. The identification result dovetailed well with cutting logging result which proves this approach is also capable of attaining a good effect when dealing with lithology identification problems in carbonate reservoirs (Figure 2).

Conclusion

Multivariate membership function discrimination method is the development for fuzzy logic and fuzzy probability theory, which sees lithologis as a linear model of discriminant factors on fuzzy domain, creates multivariate membership function using least square method and determines thresholds based on maximum membership degree law, therefore completes the identification of undetermined samples.

The test results demonstrates that this algorithm has a high identification precision and guaranteed reliability on both clastic rock stratum and carbonate stratum with significant heterogeneity and complicated structure which shows a good prospect and provides a new thought to solve complex problems on oilfield exploration and development with fuzzy theory.

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