The high-efficiency methods to identify lithology with well logging plates or a program

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Abstract. As traditional manual method to identify lithology of cored wells is laborious and lack of efficiency, two efficient methods are used this time. One method is the identification with well logging plates while another is a program. The critical values of 5 kinds of well loggings are found to be relatively stable through many trials, and some major steps should be taken before using the logs. First is to find standard rock types and their logging values. Rock types are more reliable after the observation under microscopes. The second step is to find out the logging data ranges of each rock type. The third step is to quantitatively identify rock types with the optimal critical values. In this process, the multi-array logs (M2R2) is found to be the most effective log to distinguish mudstone and oil reservoir. Low density (DEN) value is effective to distinguish the lightest matter or pores. The other two well logs, i.e. AC and CNL, can be used to distinguish whether there is limy content. Wave impedance (PD=DEN/AC) log can be a supplement when that kind of data is available, and finally all lithology is identified after that. The result that calculated from well logs with a program is similar to lithology of drilling cores. Through many trials and errors, it is finally found and proved to be a successful approach to automatically and efficiently distinguish rock types in the software of Direct and Petrel. This method is more efficient and easier to operate with a program when there are hundreds of wells, and it is a progress made that work possible. There is more widespread use in deep carbonate buried hill with this method, simply by changing the lithology codes and critical values in the program.

1. Introduction

Mostly lithology is required to be accurately identified for the selection of favorable oil reservoirs and production methods. Therefore, some technologies gradually emerged and new methods are invented, such as spider-web method [1], well-logging graphs [2], and AI machine learning method with drilling cores [3-4]. However, the method like spider-web, is actually a qualitative method with no accurate critical values. As the critical values are usually not stable, the well-logging graphs are also not a practical way to identify lithology. Therefore, a new automatic and quantitative AI lithology identification method is found through many trials and errors. 3 well logs are found to best quantitatively identify lithology, which are multi-array induction logs (M2R2), and 3-porosity well logs (AC, DEN, and CNL). They are found to be the best well logs to reflect lithology, and lithology types can be identified with a program, which is applicable in many areas.

Oil sand and shallow layers are buried at shallow depth in the study area, from 0m to 600m. The thickness and depth of fans change rapidly, and rock types are diverse. The first thick layer in Jurassic
is the oil exploration target. Several thin coal layers spread above the sand layer. The complexity of lithology increases the difficulty to identify lithology, esp. in buried hills. Therefore, our research on the lithology identification can be more easily carried out with the best critical values. To identify lithology automatically is not only essential to select favorable oil layers, but also helpful to improve some basic geology theories and methods in the future.

2. Procedures of lithology identification
There are many lithology identification methods at present [5-9]. In order to make the identification more easily applicable, a new automatic quantitative identification method is found, so we can spend less time in manual work when the lithology does not need to be so accurate. The procedures are as follows.

First is to set up a standard as a patch of highly reliable data. It is because more reliable rock types can be obtained from cores and microscopes than other information.

Second is to quantitatively identify lithology with the well logs. The array induction logs [10] (M2Rn), and 3 porosity well logs [11] (AC, DEN, and CNL) are the best logs to reflect lithology. Wave impedance [12] (PD=DEN/AC) can be used if all well logs are tested, but the program can still work without PD if the data is not efficient.

Third is the newly-invented quantitative process, with a program running in the software of Direct or Petrel. All rock types can be identified this way.

2.1. Step one: to determine accurate lithology with cores
Observing the drilling cores can help people get the most direct and reliable information. If a fan is near the provenance, all sorts of rock accumulate rapidly, so the rock types are diversified. Oil is saturated in fine sandstone like Figure 1(a) and sandy conglomerate like Figure 1(b). Coal layers are above oil sand in Figure 1(c). The lithology is complex. Through observation of 13 cored wells, it shows that fine sand is favorable for the oil accumulation, and inter layers are mostly limestone. Oil can somewhat influence the logging data, so the programs can be different in oil layers and common layers.

![Figure 1](image)

Figure 1. Drilling core photos, showing some major lithology with more or less oil: From left to right, they are separately oil-immersed conglomerates above buried hills (a), limestone with coal (b), and limestone (c).

2.2. Step two: to confirm lithology under microscope
There are lithology descriptions in the test reports of cast thin sections, and it is more accurate to determine lithology after we get to know its mineral composition. Here the lithology in cast slices is used to provide these accurate lithology data, so the rock types in cast slice repots are used as the standard.

There is also some lithology in the SEM report. Generally, the lithology information in the SEM test report is almost consistent with the lithology of drilling cores, but if the mineral composition and lithology detected by SEM are completely inconsistent, a few SEM reports may correct the lithology
to make it consistent with the mineral compositions. However, in general, cast thin sections and cores can provide more reliable lithology data.

Petrographic studies using petrographic microscope is the fundamental way of studying lithology on microscopic level. For more accuracy and detail composition, SEM studies are carried out. SEM in integration with Energy Dispersive X-ray Spectroscopy (EDS) gives the exact composition under Scanning Electron Microscope.

2.3. Step three: lithology identification with plates or a program

The determine a set of accurate lithology as the standard is important. As cores and slices are the most reliable methods to identify lithology, further analysis on the plots can be made. This is especially useful in not-cored well sections, and data of 61m cores is used as a standard. Different lithology is of difference of rock content and density, i.e. CNL: mudstone > others; AC: mudstone>conglomerate>limy glutenite, as shown in Figure 2.

Impedance (PD) is the equation of rock density and velocity (PD=DEN/AC). Due to the difference of PD, rock types show different characteristics in cross plots. Additionally, sandstone and conglomerate have some overlapped areas, which are transition types, i.e. pebbled sandstone, conglomerate, and sandy conglomerates.

2.3.1. The method to identify with data in plates. The well logs are as following:

(1) The multi-array induction M2R1 is the favorable log to quantitatively identify sandstone and mudstone. The spontaneous-potential log SP is not effective due to weak compaction of shallow layers. As for the mudstone, M2R1 is less than 8.1Ω·m. As for the muddy sand, M2R1 is between 8.1Ω·m and 25.0Ω·m. For sand bodies, M2R1 is over 25.0Ω·m.

The best well log is DEN, with the critical value of 2.27g/cm³ between sandstone and conglomerate in Figure 3 and Figure 4. Conglomerates are usually high in density due to compact and cementation while coals are low in density, less than 0.8g/cm³.

![Figure 2](image1.png)  ![Figure 3](image2.png)

**Figure 2.** Crossplot of AC and CNL shows different Mesozoic lithology in different area.

**Figure 3.** Limy rock types are especially high in density and low in CNL. Mudstone is the easiest to be identified with no overlapping area in DEN-CNLCrossplot.

(3) AC and CNL are better well logs to identify limy content [11]. The lithology is probably limestone when PD>23×10³kg/m³·s, AC<92µs/m and CNL<24%, as shown in Figure 5.

(4) The lithology is light coal when DEN<0.8g/cm³. It is a typical area full of resources with heavy oil, oil sand and coal in shallow layers.
Figure 4. Limestone and limy silts are esp. high in density (>2.4g/cm³) inside buried hills by comparing with detrital rocks above buried hills. The AC value of limestone is the lowest. The gradients of trendline are almost the same among different lithology.

2.3.2. The method to identify with a program. Through above analysis, some critical values are determined. Some key programs of this new automatic method are as follows, and the result is in Figure 6.

Mudstone=1
Conglomerate=2
Sandstone=3
Limy sandstone=4
Muddy_conglomerate=5
Coal =6
Limy_conglomerate=7

PD= DEN/AC
If (M₂R₁<8.1) lithology =1
If (25< M₂R₁ and DEN>2.3) lithology =2
If (25< M₂R₁ and 0.7<DEN<2.3) lithology =3
If (8.1< M₂R₁<25 and DEN<2.3) lithology =4
If (8.1< M₂R₁<25 and DEN>2.3) lithology =5
If (DEN<0.7) lithology =6
If (AC<92 and CNL<24 and PD>23 and DEN>2.3) lithology =7

With above similar equations, some different kinds of lithology can be automatically identified in some famous geology software, such as Petrel or Direct. This method is applicable in many areas.

If it is in lower Paleozoic, limy_conglomerate=7 need to be changed into Limestone=7 in this program, and the relative critical value also needs to be changed. Generally, this new method has its widespread use.
Figure 6. Comparison between lithology of drilling cores and identified lithology with a program.
2.3.3. Some Advantages of these two methods. Firstly, when the lithology does not need to be so accurate, it is far more efficient and applicable than traditional machine learning method.

Secondly, the lithology in further analysis can be distinguished accurately without cores, but with well logging curves, which is especially useful for wells without drilling cores.

Thirdly, quantitative lithology identification result with a program is similar to those with cores, except for some minor difference at depth. Though the depth has some difference, it doesn’t mean the well logging result is less accurate. That is to say, the logging curves show more general lithology and more accurate depth than cores.

3. Conclusions

(1) The critical values of different rock types are found to be relatively stable in 5 well logs, which are separately $M_2R_a$, DEN, AC, CNL and PD. The critical values of some lithology are 8.1Ω·m and 25Ω·m for $M_2R_a$, 0.7g/cm$^3$ and 2.3g/cm$^3$ for DEN, 92μs/ft for AC, 24% for CNL, and 23 for PD value in the research area.

(2) Array induction logs ($M_2R_a$) is the most effective log to distinguish mudstone and reservoir with the critical value of 8.1Ω·m, which is much more stable than SP.

(3) Acoustic curve (AC) and compensated neutron log (CNL) are used to distinguish whether it is not limy content or not gravel. If it is limy conglomerate, the AC should be lower than 92μs/ft and CNL lower than 24%.

(4) The rock types can be distinguished with this high-speed program. The results are similar to those of drilling cores. It’s a successful approach to efficiently distinguish rock types in the software of Direct or Petrel. There is more widespread use in deep carbonate buried hill with this method, simply by changing the lithology codes and critical values in the program.

(5) Although there are some inevitable differences between AI identified lithology and drilling core lithology, this is a good method if lithology identification is required to be finished with high work efficiency.

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