Study on automatic recognition method of continental shale lamination based on electrical imaging logging

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Abstract. In this paper, the shale oil shale stratum in Jiyang Depression is taken as the object to study the characteristics of the complex shale lithology, the frequent development of calcareous or sandy stratum, and the difficulty of manual identification. Firstly, the development characteristics of the stratigraphic layer of continental shale oil reservoir are studied. Then the electric imaging logging image is processed to restore the whole borehole wall, and then the target geological object is extracted through the operations of automatic image segmentation, connected area labeling, area contour tracking extraction and storage. Finally, the target geological objects are automatically classified and identified, the location of the continental shale texture layer is predicted, and the texture layer development index is calculated. The research results show that: after verification analysis with the core description, this method can identify the texture layer more accurately, and the coincidence rate reaches 92%. It provides support for the identification of stratigraphic facies favorable for reservoir development in the study area, and also lays a foundation for shale oil layer selection and fracturing.

Key words: electrical imaging logging, continental shale, striation recognition, image segmentation, contour extraction.

1. Introduction

The characterization and identification of terrestrial shale texture layers, the current research is mainly carried out from the geological point of view through core observation statistics, microscopic slice identification, etc. [1-4]. Attempts have been made on cross-graph recognition [5] and neural network prediction [6] on logging, but conventional logging resolution is difficult to reach the stratum level so it is important to use imaging logging for recognition. At present, it is mainly through electro-imaging human-computer interactive recognition, but it is limited by the experience of interpreters, boring and numerous manual picking operations which brings great difficulties to the identification of shale gas sandy texture. Therefore, it is very necessary to carry out fine processing for electrical imaging logging
image which can automatically identify Shale Lamina to accurately extract Lamina and reduce the workload of manual acquisition.

This paper takes the shale of shale oil reservoir in Jiyang Depression as the research object and the target geological object is extracted by performing blank band filling, automatic image segmentation, connected area marking, area contour tracking extraction and storage, etc. Then automatically classify and identify the target geological objects, predict the location of terrestrial shale lines and calculate the grain development index. Finally, compare with core description and oil test analysis which can provide technical support for the selection of favorable shale oil reservoirs.

2. Developmental characteristics of terrestrial shale strata

The continental shale oil reservoirs in the Jiyang Depression are mainly developed in the upper sub-segment of the fourth member of the Shahejie Formation in the Paleogene (the upper sub-segment of the fourth member of the Shahejie Formation), the lower sub-segment of the third member of the Shahejie Formation (the lower-segment of the third member of the Shahejie Formation) and Shahe Street Section 1 (Sha 1st Section) [7], which belongs to semi-deep lake-deep lacustrine sedimentary environment. Thin slice identification and X-ray diffraction analysis of whole rock minerals show that mud shale in Jiyang Depression is mainly composed of carbonate, clay mineral, quartz and other minerals, containing a small amount of pyrite, siderite, etc. Unlike the North American Marine Shale that has a high quartz content, the Jiyang depression shale has a high carbonate mineral content with an average content close to or greater than 50% and carbonate minerals are mainly calcite with a small amount of dolomite. TOC is 1% ~ 5% but some is more than 6%.

The shale stratum structure types are mainly bedding structure and massive structure, according to the bedding thickness, the bedding structure is mainly divided into a lamellar structure (≤1mm) and a layered structure (> 1mm), grain thickness varies, the thickness of the single layer is mostly below 1mm, and the general thickness is 0.02 ~ 0.20mm which is straight or microwave; according to the composition of the texture layer which is mainly composed of gray texture layer, mud texture layer and organic rich mud texture layer, occasionally sand texture layer. Shale lithofacies division scheme based on mineral composition, rock structure and organic carbon content [8] so the study area can be divided into more than 10 types of lithofacies and there are mainly six lithofacies: organic matter-rich laminated marl, organic matter-rich laminated marl, organic matter-rich bedded marl, organic matter-rich bedded marl, organic matter-bearing massive marl and organic matter-bearing laminated marl [7], Figure 1 is a core photograph of type 6 lithofacies.

Fig. 1 Main lithofacies types and core photo characteristics in Jiyang Depression
Statistics from oil wells in the study area show: shale oil and gas are mainly produced in organic texture-rich layered lithofacies which accounting for about 70% of the oil wells [7], it is confirmed that there is a certain relationship between lamellar facies and shale oil enrichment so the identification and characterization of shale grains are very important.

3. **Research on automatic recognition method of continental shale texture**

The method of identifying shale grains based on electrical imaging logging images is mainly divided into five steps (figure 1): (1) Electric imaging logging image full wall restoration; (2) Automatic image segmentation based on maximum between-class variance method; (3) Target Connected Area Mark; (4) Region contour tracking extraction; (5) Classification and recognition of continental shale texture.

![Flow chart of automatic identification method for terrestrial shale texture](image)

**Fig. 2 Flow chart of automatic identification method for terrestrial shale texture**

3.1. **360-degree filling of electrical imaging logging images**

Imaging logging can obtain two-dimensional images of the well bore which can reflect the structure and characteristics of the borehole wall more intuitively and clearly. Logging image visibility and intuitiveness can be used to solve geological problems that conventional logging is difficult to solve. However, due to the structure of the wellbore and the structure of the electrical imaging logging instrument, the instrument was in an open state during the measurement which caused some of the borehole wall to fail to measure coverage during scanning along the borehole wall and could not reach 100%. The generation of white bands on electrical logging images affects the quality of the image and is not conducive to subsequent image processing and recognition of geological phenomena. Filling of blank strips in electrical logging images belongs to the category of image restoration, the predecessors discussed the inverse distance weighted interpolation method and the multi-point geostatistics Filtersim simulation method, etc. [9]. In this paper, Filtersim simulation method is used to fill 360 images of electrical imaging logging. The results are shown in figure 5.

3.2. **Automatic image segmentation based on the maximum between-class variance method**

Image segmentation is an image processing technique that divides the image into non-overlapping areas and extracts the target of interest in which the most critical step is how to select a threshold to process the image into a binary image. The method of maximum inter-class variance (OSTU) proposed by Japanese scholar Otsu is a popular and effective method for automatic threshold selection so in this
paper, the maximum inter-class variance method is used to segment the image automatically and the hole information is distinguished from the background information.

The basic principle of the maximum between-class variance method is to automatically divide the grayscale histogram of the image into two parts with the optimal threshold to maximize the separation of the two parts, that is, the maximum variance, the specific implementation process is as follows [10]:

Assuming grayscale image f(x, y), the number of pixels with gray level \(i\) is \(n_i\), the gray level is (0, L), then the total number of pixels is \(N = \sum_{i=0}^{L} n_i\), the probability of gray level \(i\) appearing is \(p_i = n_i/N\), \(\sum_{i=0}^{L} p_i = 1\), the average gray level is \(\mu = \sum_{i=0}^{L} i p_i\).

The image is divided into target area \(C_0\) and background area \(C_1\) by using gray level as \(k\) threshold, is \(C_0 = 0: k\), \(C_1 = k + 1: L\), so:

The probability of \(C_0\) appearing is:

\[ \omega_0 = \sum_{i=0}^{k} p_i = \omega(k) \]  

(1)

The probability of \(C_1\) appearing is:

\[ \omega_1 = \sum_{i=k+1}^{L} p_i = 1 - \omega(k) \]  

(2)

The mean of \(C_0\) is:

\[ \mu_0 = \sum_{i=0}^{k} \frac{i p_i}{\omega_0} = \frac{\mu(k)}{\omega(k)}, \text{ among them } \mu(k) = \sum_{i=0}^{k} i p_i \]  

(3)

The mean of \(C_1\) is:

\[ \mu_1 = \sum_{i=k+1}^{L} \frac{i p_i}{\omega_1} = \frac{\mu - \mu(k)}{1 - \omega(k)} \]  

(4)

According to the theory of pattern recognition, when \(k\) is used as the threshold, the variance between the two regions is:

\[ \sigma^2(k) = \omega_0 (\mu_0 - \mu)^2 + \omega_1 (\mu_1 - \mu)^2 \]  

(5)

It can be derived from equations (1)-(4) and (5):

\[ \sigma^2(k) = \left[ \mu \omega(k) - \mu(k) \right]^2 / \{ \omega(k) * [1 - \omega(k)] \} \]  

(6)

According to the criterion of maximum between-class variance, test \(k\) within the range of gray level (0, L), the value \(k\) when \(\sigma^2(k)\) is the maximum value is the optimal segmentation threshold.

The maximum inter-class variance (OSTU) threshold method can achieve ideal segmentation effect for the image without obvious double peaks of gray-scale histogram and has wide application range. In Fig. 5, the OSTU threshold method is used to segment the image of an imaging well automatically, through the image contrast before and after processing, it can be seen that the effect of segmenting the target geological information with bright color and high resistance from the original image background is better.

3.3. Target connected area labeling

After image segmentation, the imaging image has been transformed into countless binary connected images (black and white) with texture information, next determine the method based on the connectivity of the area and mark the striations (black areas). In this paper, the method of target eight connected domain recognition is used, namely, any two points in the eight directions of the image. As long as their
pixel values are the same so they are considered connected to the same object, the specific marking steps are as follows [11]:

1. Mark the object target (black pixels equal to 1) by line scanning, the rule is to scan from point to point, from left to right and from top to bottom;

2. If the pixel at a certain point is equal to 1, then according to the counterclockwise direction to determine the upper right, directly above, upper left and front left of the point, the priority is also scanned in the counterclockwise direction from high to low;

3. If a pixel equal to 1 has a point at the top right that is also 1, so the current point and the upper right point belong to the same target object, at this time, the mark of the current point is equal to the mark of the pixel point on the upper right, then put the current point into the object where the upper right pixel is located; if the upper right pixel is not 1, in the same way, the situation of the pixel points directly above, top left, and front left is determined in order and the mark attribution of this point is determined according to the connectivity;

4. If the pixel values at the top right, top right, top left and front left of the point are not equal to 1, the point belongs to the new target object and it is attributed to the new target object.

Using the above-mentioned target eight-connected domain labeling method, the simulated connected region shown in Figure 3 was labeled and three independent regions were successfully marked in the figure.

![Fig. 3 Experimental diagram of simulated connected area labeling](image)

### 3.4. Area contour tracking extraction

After calibrating the texture layer, the individual label of each stripe layer area is obtained to be able to further calculate parameters such as the thickness and length of the texture layer and the outline of the marked texture region needs to be extracted, in this paper, the contour tracking extraction method based on area calibration is used to identify the contour of the texture.

1. Extraction method of single region contour

   The idea of extracting the contour of a single area is: first find out the points on the target contour according to certain "detection rules" and then find out other points on the boundary of the target area according to the characteristics of these points with certain tracking criteria.

   The specific implementation steps are: search according to the rules from left to right and bottom to top. Firstly find the first contour point at the bottom and store it, then use this boundary point as a starting point and 45 degrees along the upper left as the starting search direction, if the point on the upper left is the same label as the first boundary point so the point on the upper left is the second boundary point of the area; otherwise it is searched clockwise by 45 degrees until the next contour point is found. In the same way, continue to search until the line where the vertex of the area is found and then follow the upper right 45 degrees as the starting search direction, then rotate clockwise 45 degrees to search until returning to the first first contour point to complete the entire contour search.

   The contour extraction method based on region calibration is used to extract the contour of the region marked as "3" in figure 3. The processing result is as shown in figure 4, the blue solid arrow outlines the "contour route" of the area and the black dotted arrow is the "trace" judged during the target contour search process. During this search, when passing through the outline boundary points filled with red
wavy lines in Figure 4 and the 45-degree loop judgment phenomenon at the upper right will occur, that is, the program enters the "dead loop". In view of this situation, this paper improves the above contour extraction method based on area calibration, namely: Add a judgment in the search direction. If the outline boundary point appearing in the search direction has been included in the outline trajectory, then skip the outline boundary point and rotate clockwise 45 degrees on the basis of the search direction to continue the search judgment. The improved contour tracking extraction method avoids the "dead loop" phenomenon and accurately identifies the boundaries of each calibration area, as shown in Figure 4.

![Schematic diagram of contour tracking extraction method based on area calibration](image)

**Fig. 4** Schematic diagram of contour tracking extraction method based on area calibration

![Segmentation and picking of the texture layer and target geological object by electro-imaging image](image)

**Fig. 5** Segmentation and picking of the texture layer and target geological object by electro-imaging image

(2) Multi-region contour extraction

On the basis of completing the outline extraction of a single area and for multiple area targets, because the area label has been numbered so it is only necessary to perform a single area outline tracking
process for each area according to the number. Figure 5 is the effect diagram of the image full wellbore restoration, image segmentation and contour extraction of the 3202-3204m shale section of Shasanxia in FY1 well of Jiyang Depression, it can be seen from the figure that the outline of the high-resistance bright color target geological object is extracted.

3.5. Classification and recognition of terrestrial shale strata

Target geological objects still have multiple solutions, high-resistance texture layers, stripes and block objects all show bright stripes or stripes on the image. Through image segmentation and boundary extraction so numerous closed area figures are obtained, how to judge whether these closed area patterns are calcareous or sandy texture layer is very important.

Fig. 6 Flow chart of classification and recognition of texture

Fig. 7 Examples of type recognition of terrestrial shale sandy texture
The technical idea of this study to automatically distinguish the texture layers is: think of a polygon as a rectangle and find its equivalent length and width; the length and width of the grain layer are relatively large but the ratio of the length and width of the massive sandstone is relatively small. Because the coordinates of this polygon are known so first choose any point \( x_0 \) to get the distance between this point \( x_0 \) and all other points form the set \( D_n \); then the two corresponding points \((x_1, y_1)\) and \((x_2, y_2)\) are rotated in the same direction with a fixed step length when the \( D_n \) is maximal so the distance set of the two points is obtained; the maximum value of the two-point distance set \( D_n \) is determined as the equivalent length \( L \) of the polygon; next find the area \( S \) of the polygon according to the integration principle and use \( S/L \) to find the equivalent width \( H \) of the polygon; finally, find the ratio \( K \) of \( L/H \) and define \( K > 5 \) as the texture layer (Figure 6). Figure 7 is an example of texture recognition for well FY1, it can be seen that there are 4 positions such as 3154.0-3154.5m, 3157.1-3157.3m, 3157.35-3157.45m., and the \( K \) value is significantly greater than 5, and the recognition becomes a band. At depths of 3155.45m, 3156m, 3158.4m, multiple calcareous or sandy texture layers were developed and the \( K \) value was significantly less than 5.

4. Case analysis and discussion

The texture characteristics of shale oil reservoirs in Shengli Oilfield were analyzed and compared with the core description results, as shown in Figure 8. It can be seen from the diagram that the method of this paper has identified the lithofacies strata described by 13 cores and identified 7 layers of lamellar or stratified lithofacies, 5 layers of massive lithofacies finally 1 layer less than the description of the core which is statistical coincidence rate of 92% , give or take 8% .

Fig. 8 Comparison and Verification Diagram Between Identification Result of Continental Shale Reservoir Lamina and core observation

5. Conclusion

(1) Based on a series of methods such as Filersim simulation of omnidirectional wellbore restoration, automatic image segmentation with the largest inter-class variance method, target connected area
labeling, contour tracking extraction and texture classification recognition, the core comparison verification analysis can more accurately identify the layer or grain layered lithofacies.

(2) There are a large number of stratigraphic facies in mud shale reservoirs in Jiyang Depression. Prospecting practice has proved that there is an inevitable connection between the stratigraphic facies and shale oil enrichment and high-production wells so the identification of the stratigraphic layer based on imaging logging is beneficial to the next favorable reservoir Selection of intervals.

(3) Since the thickness of the stratum is much smaller than the resolution of electro-imaging logging (5mm), the result of the stratum recognition can only reflect the relative change of the longitudinal development of the stratum. The next step of the study should be combined with other information such as element logging to identify the type of the stratum and evaluation.

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