Grain Size information Extracting from Sand Conglomerate Reservoir based on FMI Data:A case study of sha4 formation in Dongying Sag

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Abstract: The evaluation of rock phase and reservoir property is the key problem to be solved in the exploration of deep sand conglomerate. The study of rock phase information is only in the qualitative stage according to the FMI logging data with the results are mainly image-lithologic models. It is urgent to extract gravel information based on image analysis. FMI image can be transformed into a vertical core gravel image after the operation of grayscale, blind area filling, image filtering, image segmentation and gravel extraction. The maximum gravel size is selected as the rock phase marker, and the statistical relationship of the conventional logging curves with resistivity, GR and density is established. It can provide a useful supplement for petrographic classification.

1. Introduction
As a complex formed by rapid accumulation of multi-period fan bodies, glutenite reservoirs often show characteristics such as messy internal structure, strong heterogeneity and complicated reservoir forming rules (Yan Jianping, 2011). Exploration practice of glutenite bodies in the north of Dongying Sag, Jiyang Depression shows that the source rocks adjacent to the fourth member of Shahejie Formation are abundant and the lateral sealing of glutenite bodies provides the conditions for effective trapping. Therefore, exploration is restricted and the main challenge at work is effective reservoir identification. For a given area, except for structural, fluid and diagenetic factors, the main factors influencing the effectiveness of deep glutenite reservoirs are lithofacies types and reservoir physical properties under their control (Li Junliang, 2008). Exploration practice shows that gravel Reservoirs are generally undeveloped, reservoirs pebbled sandstone and gravel sandstone are well developed. FMI imaging logging data, as a sharp weapon for the study of facies and sedimentary features of glutenite, has become an indispensable tool in the study of glutenite facies belts. In the past, the research of lithofacies information based on the electrical imaging logging data only stayed in the
qualitative stage. The achievements mostly focused on the establishment of the image-lithology model based on electrical imaging and lack of quantitative characterization (Zhang Zhansong, 2003; Wu Wensheng, 2000; Chen Ganghua, 2001; Zhang Longhai, 2006). Taking the exploration of the Yanjia glutenite body in the north belt of Dongying for example, taking the vertical image processing of a single well as an example, the vertical gravel particle diameter curve of the glutenite body was extracted and the conventional logging with imaging scale was optimized. The resistivity, density and combination gamma ray neutron laterolog and other three curves to build a function of the grain size and sensitive logging curve in the study area, which can assist the lithofacies division of glutenite body and provide the basis for detailed interpretation and evaluation.

2. Regional Geological Survey

The steep slope belt in the northern part of Dongying Depression is a near-east-west tectonic belt dominated by the Chennan shovel fault. Due to the long-term tectonic movement and weathering, the steep slope belt is the main development zone of the deep glutenite body in Dongying Sag. The Yanjia oilfield is structurally located in the eastern section of the northern steep slope with the southern side of Chenjiazhuang convex, the paleogeomorphology of ditch and beam controlling the development and distribution of various fan bodies (Lu Guoming, 2010). Provenance and geomorphology, sedimentary environment and other factors make the steep slope show the characteristics of complex changes in lithology, low maturity of structure and composition, complex logging response and little obvious rock electric law.

The fourth member of Shahejie of the Yanjia Oilfield mainly develops deep-lying nearshore subaqueous fans. The burial depth ranges from 3,000 to 4,000 meters. The main lithologies are conglomerate, gravel sandstone, pebbled sandstone and medium-fine sandstone. The observation of thin slices shows that the main mineral components of gravel are quartz and feldspar, which are influenced by the parent rock of gneiss. The content of potassium feldspar in glutenite of the Yanjia is relatively high. According to physical property analysis, the porosity is mainly distributed between 3% and 15%, and the permeability is between 0.1mD and 10mD, which belongs to the reservoir with low porosity and low permeability [8].

![Fig. 1 Sketch of the tectonic zoning of Dongying north zone [1]](image-url)
Figure 2 shows the oil level under different lithology statistic charts, we can see that the oiliness of gravel sandstone and pebbled sandstone is the best, followed by conglomerate. Fig. 3 shows the relationship between porosity and permeability under different lithology conditions. From the statistics, it can be seen that the porosity of the gravel reservoir gradually becomes smaller as the lithology becomes thicker. Physical properties and rock structure are related. At the same time with the analysis of Figure 2 shows that the physical properties of reservoirs have an important impact on oiliness, with better physical properties, oil levels gradually increased. Since the identification of effective reservoirs is a constraining problem for deep glutenite bodies and the development of effective reservoirs is closely related to the lithofacies facies types and the properties of specific facies belts, the crux of the problem lies in the division of lithofacies. The key to the phase is to get the gravel particle size curve.

### 3. Gravel particle size extraction principles and methods

The FMI, a downhole conductivity image measured by Schlumberger Electroimaging Instrument, measures the well's circumference either array-wise or rotational-sweep through 192 button electrodes of a downhole tool to acquire longitudinal, circumferential, radial stratigraphic information, and then obtain the two-dimensional image of the well bore or the three-dimensional image within a certain depth of investigation around the borehole by means of image processing techniques (depth correction, velocity correction, balance) (Zhou Lunxian, 2008). FMI commonly used color palette for the black - brown - yellow - white, subtle changes in color represents the lithology and physical changes, the color from dark to dark, respectively representing the conductivity from high to low.

In general, gravel diameter gradually decreases from fan-to-fan and then to fan-end, and the heterogeneity gradually decreases. Therefore, the change of gravel size can be used as a reference index to distinguish different lithofacies. Due to the poor conductivity of gravel, it appears as bright patches on the electrical imaging, which is obviously different from the background of the electrophotographic image. Therefore, the graphene information can be extracted by the digital image processing method. The specific steps are as follows:

#### 3.1. Step 1 – grayscale

Grayscale processing refers to the process of converting a color image into a grayscale image. Since the color of each pixel in the color image is determined by the three components of R, G, and B, and there are 255 variation values for each component, the processing of the color image increases an enormous workload. Therefore, converting to a grayscale image becomes the usual choice. Grayscale image refers to a special image with the same three components of R, G, B. Converting the image to grayscale can greatly reduce the amount of calculation, but it still retains the whole image and local colorimetric and brightness levels feature. In this study, 8-bit grayscale images were selected, and the grayscale range was [0,255]. Based on the RGB value of color image, the gray value of the corresponding pixel is calculated by formula (1).

\[
\text{Gray} = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B
\]
After the grayscale, the image from Figure 4 (a) to Figure 4 (b).

![Fig. 4 Extraction steps of gravel in sandy conglomerate](image)

3.2. Step 2 - blind area filling

For the electrical logging imaging, there are some blind spots in the image due to the shielding of the plate, showing a white band, as shown in Figure 4 (a). Image repair methods are mainly nonlinear filtering methods, Bayesian methods, wavelet and spectral analysis methods, texture-based repair methods and multi-point statistical methods (Nie Tuxian, 2011). In this study, multi-point geostatistics was used to fill the reservoir. This method was originally used in the field of geological modeling to treat continuous geological entities at reservoir scale. The basis of the multipoint geostatistical method is to replace the variogram in the two-point geostatistics with the training image. The basic idea is to extract the image features of the features from the training images and then restore the patterns to the final model. Compared with the traditional two-point correlation function, this method can restore the long-range correlation in the electrical imaging log image, so the repaired image more accurately reflects the actual geological environment.

The Filtersim simulation algorithm is a filter-based multi-point geostatistical approach that uses a set of filters to classify the various patterns of a training image. Training image variable types can be either discrete or continuous. Based on the template classification, Filtersim simulates the simulated area. A filter is a data template with weights at each pixel location. When you place a filter on a training image, you get the filter score in the data template area, which can be considered as the sum of the filter scores for the region training image. The filter transforms each pattern in the training image into a filter score space so that the dimensions of the training image are greatly reduced. In the process of simulation, the filter is used to obtain the filter score of the data event in the area to be simulated, the mode in the training image that is closest to the data event, and then "paste" the mode into the area to be simulated. Due to the filter used, the training image dimension decreases, so the simulation speed becomes faster. After filling the blind spot, the image changes from Fig.4 (b) to Fig.4 (c).

3.3. Step 3 - Image Filtering

Image filtering is to suppress the noise of the target image while preserving the image detail characteristics (Xiao Mengqiang, 2012). FMI images are often contaminated with noise during downhole electrode measurements, data transmission and conductivity imaging, affecting the overall image quality. These noises often appear as isolated pixels or pixel blocks in the image, but appear as the maximum or the minimum value in the digital information, forming the interference of light and dark spots, affecting the extraction and analysis of digital information. In 1971, J.W. Jukey firstly applied the median filter in one-dimensional signal processing (time series analysis) and later in two-dimensional image signal processing. Under certain conditions, the median filter can overcome the ambiguity of the image detail generated by the linear filter, and is most effective in filtering out the
pulse interference and the image scanning noise. As the actual operation, the filter does not require the
statistical characteristics of the image, making it more computationally efficient.

The median filter is to build a sliding window composed of an odd number of pixels, the gray value
of the center of the window is replaced by the median value of each point in the window. Assuming
there are 5 points in the window, the gray values are 30, 50, 150, 100, and 110 respectively, then the
median of each point in the window is 100, then the gray value of the center point in the filtered
window becomes 100. Expressed as a mathematical formula

$$y_i = \text{Med}\{f_{i+v}, \cdots, f_i, \cdots, f_{i-v}\}, \quad v = \frac{m-1}{2}$$  \hspace{1cm} (2)

Where m is the length of the window, which is an odd number. For some images with more details,
you can use different median filters multiple times, and then combine the results as output, so as to
obtain better smoothing and edge protection. After image median filtering, effectively remove the
target and background noise, while preserving the image-specific geometric and topological features,
as shown in Figure 4 (d).

3.4. Step 4 - Image Segmentation

Image segmentation refers to the extraction of a specific, unique region of an image for the purpose of
identifying and analyzing the target. As the key technology of image processing, image segmentation
has proposed nearly a thousand kinds of segmentation algorithms since the 1970s, but so far no
general segmentation theory has been put forward. Grayscale threshold segmentation as a parallel
regional technology, the most common application in image segmentation. Assuming that the
grayscale of the original image is a function of the pixel position \( f(x, y) \), an appropriate grayscale
value is determined as a threshold \( t \) according to certain criteria in \( f(x, y) \), and the
image \( g(x, y) \) segmented according to the above method can be expressed as formula (3).

$$g(x, y) = \begin{cases} 
1 & f(x, y) \geq t \\
0 & f(x, y) < t
\end{cases}$$  \hspace{1cm} (3)

The key of this method is to determine the threshold. This study uses an adaptive threshold
technique to segment the gravel area, as shown in the red area in Figure 4 (e).

3.5. Step 5 - Gravel extraction

The gravel in the segmented image is stored as a pixel. To account for gravel content and size
distribution, it is necessary to characterize isolated pixels as gravels. The Hoshen-Kopelman algorithm
is a grid-based tagging algorithm that has two states for each grid: "occupied" and "free", and the grid
in the algorithm is the same as the pixels in a two-dimensional image. In the gravel cluster labeling
algorithm, the grayscale pixel state is set to "occupied" and the remaining pixels are set to "free". If
there are no pixels in the area around the gravel pixel that are "occupied," the gravel pixel is treated as
a new gravel cluster, giving a new gravel cluster mark. If there is a pixel in the state of "occupied"
around the gravel pixel, then the gravel pixel and "occupied pixel" are considered as a gravel cluster,
labeled with the same gravel cluster. If there are multiple gravel around the gravel pixel in the state of
"occupied", the flag with the lowest gravel cluster mark in the "occupied" state is selected as the gravel
cluster mark. Pixels with the same gravel cluster mark are considered as a gravel. According to the
resolution of three-dimensional digital core, the area (two-dimensional) or volume (three-dimensional)
of gravel can be obtained by counting the number of pixels (two-dimensional) or three-dimensional
pixels Circle or ball radius. In Figure 5 (b), the gravel with gravel cluster labeled 3 contains 8 pixels.
Gravel distribution after H-K labeling is shown in Fig. 4 (f). Different colors only distinguish different gravel bodies, which have nothing to do with size. Parameters such as gravel number, shape, particle size and the like can be obtained based on gravel-labeled images.

4. Electrical imaging logging and conventional curve modeling

4.1. Parameter Optimization

After the image processing and gravel extraction were performed on the 3500-3730 meters vertical section of the well Y22-22, the parameters such as the number of gravel, the average gravel size, the maximum gravel size and the minimum gravel size were obtained. In the process, there are some details that need special instructions, one is the depth of data statistics interval. Taking into account the sampling interval of electrical imaging and the characteristics of glutenite, the depth interval of 1 meter is considered as the data, that is, the maximum gravel size refers to the maximum gravel size within a depth of 1 meter, and so on. Second, the grayscale image size and the actual size of the relationship conversion. The length of the well circumference can be calculated according to the borehole diameter of 6.5 in. The actual size is matched with the width of the electrophotographic image to obtain the actual size corresponding to each electrophotographic pixel, which can be converted to the size parameter of the gravel. It has not been considered whether the gravel information can be completely reflected by the electrical imaging. In view of the main purpose of this study is to extract gravel relative changes in particle size, so this factor can be ignored; third is the particle size optimization problem. Considering that the gravel number and gravel average particle size in the treatment interval weaken the heterogeneity of glutenite to a certain extent, the maximum gravel radius is adopted as the grain size parameter.

4.2. General Logging Model Building Based on Gravel Information

Logging curve is one of the most intuitive means to reflect the lithofacies change of reservoirs. Due to the limitation of acquisition cost, not all wells have electrical imaging logging. Therefore, gravel information extracted from electrical imaging data is used as calibration to establish gravel maximum grain Quantitative relationship between path and conventional logging is particularly important. Due to the heterogeneity of reservoir, radioactivity, lithology and oiliness, the log response of glutenite in the Yanjia area is extremely complicated. In order to characterize the relationship between conventional logging and gravel information, it is necessary to optimize the information of gravel sensitive logging characterization parameters. The single-correlation analysis of the maximum gravel size and the conventional well logging response was carried out one by one. Finally, the resistivity, combination gamma ray neutron laterolog and density were selected as modeling parameters. The larger the gravel diameter, the thicker the rock facies, the larger the rock density and the higher the resistivity. The rock size is positively correlated with the resistivity and density. The smaller the rock...
size, the smaller the lithology. Therefore, the combination gamma ray neutron laterolog is higher, the particle size and combination gamma ray neutron laterolog is inversely related.

Table 1. A sample of gravel data from FMI image processing

| Depth (m) | Identify the number of gravel (n) | The average particle size (cm) | Maximum particle size (cm) | The smallest particle size (cm) |
|-----------|----------------------------------|--------------------------------|---------------------------|-------------------------------|
| 3500      | 39                               | 1.18                           | 4.01                      | 0.26                          |
| 3501      | 60                               | 1.37                           | 7.32                      | 0.21                          |
| 3502      | 11                               | 1.51                           | 3.18                      | 0.15                          |
| 3503      | 44                               | 1.19                           | 4.43                      | 0.15                          |
| 3504      | 81                               | 0.97                           | 5.09                      | 0.15                          |
| 3505      | 41                               | 0.82                           | 3.38                      | 0.15                          |
| 3506      | 43                               | 1.33                           | 5.21                      | 0.15                          |
| 3507      | 60                               | 1.14                           | 8.70                      | 0.15                          |
| 3508      | 23                               | 2.25                           | 9.40                      | 0.15                          |
| 3509      | 46                               | 1.27                           | 6.70                      | 0.15                          |
| 3510      | 55                               | 1.17                           | 7.05                      | 0.15                          |
| 3511      | 60                               | 1.07                           | 5.08                      | 0.15                          |
| 3512      | 24                               | 1.94                           | 7.11                      | 0.15                          |
| 3513      | 89                               | 1.27                           | 8.73                      | 0.15                          |
| 3514      | 41                               | 1.68                           | 9.77                      | 0.15                          |
| ...       | ...                              | ...                            | ...                       | ...                           |

Taking the maximum gravel size extracted by electrical imaging as the dependent variable, the statistical regression was conducted with the resistivity, the combination gamma ray neutron laterolog and the density as the independent variables. The following statistical relationship was obtained according to the layer-layer correspondence modeling method:

\[
D_{\text{max}} = 2.509 \times \text{DEN} - 0.01 \times \text{GR} + 0.118 \times \text{RD} - 3.376 \quad R^2 = 0.8615
\]  

Inter: 
- \(D_{\text{max}}\) — Gravel maximum particle size, cm; 
- \(\text{DEN}\) — Reservoir measured density log, g/cm\(^3\); 
- \(\text{GR}\) — Reservoir measured natural gamma value, API; 
- \(\text{RD}\) — Reservoir measured deep resistivity value, Ω.m.

Fig. 6 Accuracy of model to compute maximum grain size of gravel
The accuracy of the model was tested. The maximum gravel diameter extracted by electrophotography was plotted on the horizontal axis, and the maximum gravel diameter calculated on the basis of equation (4) was taken as the vertical axis for accuracy analysis (see Figure 6). On both sides of the 45° line, the requirements for model accuracy are met.

4.3. Application examples and analysis

Based on the statistical relationship of formula (4), well logging data of Y22-22 well are processed in single well, as shown in Fig.7. The second is the density curve, the third is the combination gamma ray neutron laterolog curve, the fourth is the resistivity curve. The "maximum particle size of rock" in the sixth channel is the calculation result of electric imaging extraction. "Calculate the largest particle size" is the result of calculation according to formula (4). From the data trend and numerical matching, the relationship between the two is good, As a reference for calculating the particle size in the next step.

![Fig. 7 Processing results of rock grain size of well Y22-22](image)

The logging data of 3500m-3700m in Well Y22-22 of the study area are processed and the gravel information of different lithofacies is extracted (see Table 2). Through the correlation with core, electrical imaging, logging lithology calibration and physical properties of conventional core analysis data scale, the following lithology identification criteria are formulated (see Table 3). It is important to note that the resolution of the electrical imaging (theoretical maximum resolution is about 0.5 cm) is limited by the definition of the gravel size range. This standard is therefore only used to differentiate the grading curve levels calculated from electrical imaging or conventional logging data. After the grain size curve is obtained based on conventional well logging data, the lithology of different types of conglomerate can be identified according to the classification in Table 2. From conglomerate, gravelly sandstone, gravelly sandstone to medium-fine sandstone, the grain size gradually decreases and gravel Sandstone physical properties to a certain extent, better than pebbly sandstone.
Table 2. Sand conglomerate data based on FMI image processing

| Original FMI image | Gravel information extraction | Gravel information | Lithofacies |
|--------------------|-------------------------------|-------------------|------------|
|                    |                               | depth: 3520m-3521m | gravel     |
|                    |                               | gravel number: 36 |            |
|                    |                               | average granul diametre: 7.65cm |            |
|                    |                               | maximum granul diametre: 12.22cm |            |
|                    |                               | smallest granul diametre: 0.15cm |            |
|                    |                               |                   |            |
|                    |                               | depth: 3525m-3526m | Gravel sandstone |
|                    |                               | gravel number: 94 |            |
|                    |                               | average granul diametre: 1.39cm |            |
|                    |                               | maximum granul diametre: 7.38cm |            |
|                    |                               | smallest granul diametre: 0.15cm |            |
|                    |                               |                   |            |
|                    |                               | depth: 3519m-3520m | pebbled sandstone |
|                    |                               | gravel number: 30 |            |
|                    |                               | average granul diametre: 1.23cm |            |
|                    |                               | maximum granul diametre: 4.07cm |            |
|                    |                               | smallest granul diametre: 0.15cm |            |

Table 3. Classification of gravel information based on electrical imaging extraction data

| lithology           | gravel number (n/m) | maximum granul diameter (cm) | average granul diameter (cm) | Porosity (%) | homogeneity |
|---------------------|---------------------|------------------------------|-----------------------------|--------------|-------------|
| conglomerate        | <50                 | >10                          | >2                          | 3%-7%        | bad         |
| gravel sandstone    | >50                 | 6-10                         | 1-2                         | 5%-10%       | middle      |
| pebbled sandstone   | >50                 | 4-8                          | 1-2                         | 3%-16%       | middle      |
| Sandstone / Shaly   | <50                 | <4                           | <1                          | 3%-9%        | well        |

5. Conclusion
FMI images can be converted into gravel information vertical profiles that include changes in gravel particle size based on grayscale, dead-zone fill, image filtering, image segmentation, and gravel extraction. By choosing the largest particle size as the indicator of lithofacies, the quantitative statistical relationship between the maximum particle size of rock and the conventional well logging curve was established. The proposed criterion of lithofacies division was established by using electrical imaging scale.

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