A Identification Method of Logging Mud Ratio is Based on Deep Learning

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Abstract. During the logging, the sand ratio of rock debris is an important index to describe the oil content of the well at a certain depth, which can reflect the well depth of the bottom of the drill rod in different kinds of rock layers. The traditional calculation method of ratio sandstone to mudstone is artificial recognition, which takes a long time and has a low accuracy. This text applies the deep learning method to realize the automatic recognition calculation of ratio sandstone to mudstone, which has low cost, fast speed and high accuracy, and is suitable for practical field application. This text first uses the morphological watershed algorithm to divide the rock chips and obtain the rock particles, and then uses the convolutional neural network to calculate ratio sandstone to mudstone.

Keywords: Ratio sandstone to mudstone, deep learning, convolutional neural network, watershed algorithm.

1. Introduction
During the well logging process, the rock debris continuously remove the debris broken by the drill bit and returned to the wellhead during the drilling process with the mud, extract the debris, and analyze the ratio sandstone to mudstone after cleaning. The ratio sandstone to mudstone describes the rock formation of the stratum where the drill is located. Experts enable the transmitted rock debris to restore the underground rock structure in chronological order. Calculating the ratio to determine the appropriate mining probability and oil content of the underground layer.

In the process of traditional logging, the method of calculating the ratio sandstone to mudstone is to manually estimate the rock debris transmitted back to the ground, and estimate the number of particles of the mudstone and sandstone. The calculation method of manually calculating ratio sandstone to mudstone takes long time and has low accuracy, so it is of great significance to realize the standardization and automation of calculating ratio sandstone to mudstone. This paper first uses an improved morphological watershed algorithm to realize image segmentation. Convolutional neural networks are used to distinguish between the two post-segmented rock particles. Convolutional neural network is applied to extract image characteristics and complete image classification, which can automate the realization of ratio sandstone to mudstone calculation.
2. Adhesive image segmentation method

2.1. Morphological watershed algorithm

The watershed algorithm is a mapping operation from two-dimensional image to three-dimensional topographic map. The three-dimensional topographic map was established to be positively correlated to altitude and gray scale values. This text uses the simulated water immersion method, so the points with low gray scale form the valley. Water in the valley as the water level rises, the water in the various valleys has a tendency to converge. To prevent the water from coming together, a dam was established between the valleys, known as the watershed. The traditional watershed algorithm is sensitive to gray value and is easy to cause excessive segmentation, so the improved morphological watershed algorithm is used. Morphological watershed algorithm is that before the traditional watershed algorithm operation, the morphological corrosion and expansion of the original image are performed to remove the noise, and then conduct the distance transformation. The distance transformation is the computational minimum distance between each point and background in the picture, with a large computational amount. In the actual calculation process, only the local minima are calculated at each time. The global minimum is essentially a superposition calculation of the local minima, and hence a secondary scan of the image to obtain an approximate distance image. The distance transformation adopts Mahalanobis distance, and the formula is expressed as:

\[ d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \] (1)

The image center obtained after the distance transformation is called determining the foreground. The determine background as the background after the expansion operation of the picture. After the known determined background and the determined foreground, the rest of the image is known, called an unknown region. The unknown region is determined by the difference between the original image, the determined background and the determined foreground. Mark the unknown area, and use the watershed algorithm to get a better segmentation image.

2.2. Adached image segmentation based on the morphological watershed algorithm

The fragment image is characterized by not smooth and the edges of the image are not obvious. Therefore, for the rock chip image, the image edge detection in the digital image processing is selected to separate the unbonded image in the image. The image is first filtered in Gaussian ways to remove the noise during the image generation process. Then the three-channel BGR image is converted to a grayscale image. Extract the image outline and draw the smallest rectangular box, cutting out each rectangular box of the image. When separating the rectangular frame, some rock debris was found to bond. As shown in Figure 1: left is adached image and right is unbonded image.

![Adached image and Unbonded image](Figure 1. Rock detrital particle image.)
The classification model determines whether the image is a cohesive image. If the image is a viscous image, it needs to be split by the morphological watershed algorithm. The main contents of the segmentation algorithm include morphological operation, distance transformation, and watershed algorithm. First morphological operations on adhesion images. In Figure 2, from left to right, a binary image, a corroded image, and an expanded image.

![Figure 2. The morphological operations.](image)

The image after the morphological operation is subtracted from the original image to obtain the boundary. The distance from an arbitrary point to the nearest background point in the binary image is calculated. The marking result is modified using the distance transformation and the watershed is divided. The segmentation result is shown in Figure 3:

![Figure 3. Image segmentation.](image)

Redivide the divided rock debris and split each subimage. If the adhesion image appears, repeat the above steps for adhesion segmentation until the image is not attached.

3. Sand and mud recognition based on the convolutional neural network

3.1. Convolutional neural networks

The basic idea of deep neural network is to perform multi-layer representation and analysis through multi-layer network. A Convolutional neural network is a deep neural network with a convolutional structure that reduces the amount of operations based on the deep network and saves great memory to some extent. The structure of convolutional neural networks includes convolutional layer, pooling layer, full connection layer, and output layer. As shown in Figure 4.
Figure 4. Structural diagram of convolutional neural networks.

The main part of the convolutional neural network is the convolution operation, which enables the neural network to better extract the image characteristics for completing the classification. Simply put, use the convolutional core to convert the original image into pictures that can contain the original features but less data. The main principle of convolution is the filtering operation of the image, and hence the convolution core as the filter, which is the convolution operation of the convolutional core for the sliding window on the original picture. The pooling layer can not only extract the image characteristics, but also reduce the dimension of the image.

The activation function, the ReLU and Softmax functions, are used in this paper, where the ReLU function is used on the convolutional layer, and the expression is:

$$ReLU = MAX(0, x)$$

(2)

The function softmax, activation function softmax selected at the last layer of this paper is generally used for multi-classification. It maps multiple neuron output results into the (0, 1) interval, and can be understood as probabilities of this class, with the Softmax function expression being:

$$S_i = \frac{e^i}{\sum_j e^j}$$

(3)

The $S_i$ expression model predicts the probability of the i category, obtaining the maximum probability of the nodes, as the target of the prediction. Convolutional neural networks use weight sharing and dropout to reduce model complexity and reduce model parameters to prevent model over-fitting.

3.2. Classification of sandstone and mudstone particles

Data processing: Take 500 images of sandstone and mudstone each, and detect the quality of the image. Remove unclear in sandstone classification, too many distractions in images, and too heavily exposed in sandstone. There are too few pictures for convolutional neural networks, so image enhancement is required. Image enhancement includes translation, rotation, and cutting, with a total of 10 images. Establish convolutional neural network model architecture as in Figure 4.

The network mainly includes: convolutional layer, pooling layer, and full connection layer. To prevent overfitting from joining the dropout layer, the dense layer is finally added. The loss function selected categorical_crossentropy, for 100 model parameters with the highest accuracy in the epoch, save test set.

4. Ratio sandstone to mudstone calculation calculation

4.1. Algorithm flow chart

The implementation steps of the algorithm are as follows, first extract the outline of the rock chip image, form the grain image, send the grain image to the convolutional neural network, then judge
whether the grain image is cohesive, if the image is not attached into the sediment to the classification model, judge the rock type; if the image is a cohesive image, the morphological watershed algorithm is used. Put the divided rock particles into the classification model. Use the convolutional neural network to classify sandstone and mudstone, calculate the number of sandstone and mudstone, and calculate the sand-mud ratio.

![Algorithm Flowchart](image)

**Figure 5.** The algorithm flowchart.

### 4.2. Experimental results

The measure of the model is the accuracy of the training and validation sets, and the below is the model accuracy and loss function of training 100 epochs.

![Function of training and validation](image)

**Figure 6.** Function of training and validation.

The accuracy of the training and test set reached around 0.9 after 20 epochs and showed higher image classification. The loss function of the test set has been in a state of gradual convergence, while the training set is around 20 epochs, and the loss function begins to be stable. The classification model of mudstone sandstone has good results.

Using the established segmentation and classification model, three pictures of rock chips were randomly selected to test the effect of the model.
The image contour of rock debris was extracted by the convolutional neural network, dividing the cohesive images by morphological watershed algorithm. Then the divided rocks were introduced into the sand and mud convolutional neural network classification model to calculate the number of sandstone and mudstone, and the sand and mud ratio. The experimental results are as shown in Table 1:

|                | Simulation diagram (I) | Simulation diagram (II) | Simulation Diagram (III) |
|----------------|------------------------|-------------------------|--------------------------|
| Number of sandstone | 18                     | 17                      | 12                       | 12                       | 14                       | 16                       |
| Number of mudstones | 53                     | 54                      | 44                       | 41                       | 67                       | 65                       |
| Sand and mud ratio  | 0.34                   | 0.31                    | 0.27                     | 0.29                     | 0.21                     | 0.25                     |

The experimental results of Table 1 show that a few error of sandstone and mudstone occurred in the model, and a small amount of rock was not identified. However, the error in the experiment had little impact on the ratio sandstone to mudstone, so the recognition method is better.

5. Conclusion
In order to adapt to the future development trend of combining industry and intelligence, the logging rock debris image is identified according to the classification and segmentation algorithm.

(1) Through the morphological watershed algorithm, the adhesion problem in the rock debris was solved. Extract individual rock particles to achieve rock granulation.

(2) Through model training using the convolutional neural network, the divided debris particles were imported into the convolutional neural network classification model, and the verification set accuracy is up to 0.95833.

(3) The automatic identification of sand-mud ratio is realized by the algorithm of segmentation classification, and the method can be used for specific gravity analysis of other mixed particles.

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