

A Rock Structure Recognition System Using FMI Images

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Abstract. Formation Micro Imager (FMI) can directly reflect changes of wall stratum and rock structures. It is also an important method to divide stratum and identify lithology. However, people usually deal with FMI images manually, which is extremely inefficient and may incur heavy burdens in practice. In this paper, with characteristics of rock structures from FMI images, we develop an efficient and intelligent rock structure recognition system by engaging image processing and pattern recognition technologies. First, we choose the most effective color and shape features for rock images. Then, the corresponding single classifier is designed to recognize the FMI images. Finally, all these classifiers are combined to construct the recognition system. Experimental results show that our system is able to achieve promising performance and significantly reduce the complexity and difficulty of the rock structure recognition task.

Keywords: FMI, rock structure, feature extraction, multiple classifier system

1 Introduction

As the oil and gas exploration becomes gradually complicated, the traditional well logging method has many problems such as they are difficult in recognizing effective layers and also hard to estimate reserves parameters. These problems seriously influence the objectivity of reserves assessments. In contrast, Formation Micro Imager (FMI) technology can provide rich information on fractured reservoirs, and most importantly it can be applied to identify fractured reservoirs qualitatively and can help explain them quantitatively [1-2]. Some FMI image samples are as shown in Fig.1.

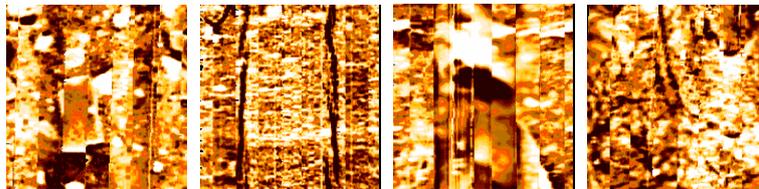


Fig. 1. FMI images

However, the most commonly way to deal with FMI images in China is still dependent on manual processing, which hence incurs heavy workload and inefficiency. Moreover, the results obtained manually are usually affected by the experience of the operators and may not be consistent in practice. Furthermore, it is fairly difficult to make fully use of FMI images for agencies without enough expertise and experienced geologists [3]. Hence, it is of great significance to develop an efficient intelligent recognition system using FMI images, for promoting oil and gas exploration.

In this paper, by applying pattern recognition technologies, we develop a rock structure recognition system based on FMI images. This system extracts useful features effectively and then recognizes rock structures with FMI images automatically. First, we chose the color and shape features for rock images. Then, the corresponding single classifier is designed to recognize the FMI images. Finally, all these classifiers are combined to construct the recognition system.

The rest of the paper is organized as follows. Section 2 describes the recognition system framework. And experimental results of the recognition system are shown in Section 3. Finally, some conclusions are drawn in Section 4.

2 System Framework and Analysis

2.1 System Framework

Rock structures can be classified by the proposed recognition system with image processing and pattern recognition technologies. This system includes three main modules, i.e., image pre-processing, feature extraction, and structure recognition, which is shown in Fig.2.

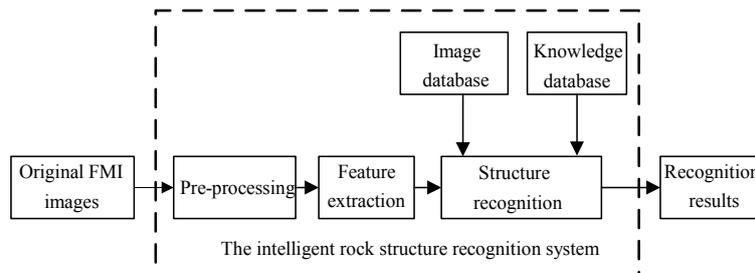


Fig. 2. The rock structure recognition system framework

The image pre-processing step is to filter out the noise. The main task for feature extraction is to extract characteristics of the rock, such as color and shape features. Structure recognition applies and combines multiple classifiers (k-nearest neighbor classifiers). Image database and knowledge database mainly provide the references for recognizing images and categories of the rock structures. In this paper, we will mainly focus on feature extraction and the combination of multiple classifiers.

2.2 Feature Extraction

Feature extraction is a very important step, and it heavily affects the final recognition accuracy. Following many other systems, we select color and shape features for our recognition system.

In fact, shape describes the important difference among the rocks with different structures. Traditional methods merely exploiting color features cannot efficiently categorize rocks. As a result, combining color and shape features can largely improve the recognition accuracy. In this paper, rock structure features include the proportion of white color accounted in the image and the shape information.

2.2.1 Color Feature Extraction

From different rock structures, we find that particles distribute uniformly and are always white, which is an important feature of some rock structures.

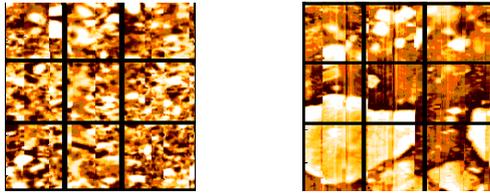


Fig. 3. Particle distribution comparison

As it is shown in Fig.3, the particles in the left image are uniform in distribution, while the particles in the right one are very uneven in distribution. Consequently, we propose the following color feature extraction method. The block FMI image is divided into blocks and the white color proportion in every one is counted. After that the proportion values between the blocks are compared and calculated as features. If the values are even, the distribution is uniform; otherwise, it is not uniform.

2.2.2 Shape Feature Extraction

To a large extent, shape features can reflect the structure information of objects, and most efficient features for classifying are mainly composed of shape characteristics [4-5]. There are a lot of methods for shape feature extraction. In the early experiments we tried to use traditional edge detection methods to extract structure information. The FMI images are processed with Sobel and Canny transformation, and then the edges of the images are acquired. The results are as shown in Fig.4. From Fig.4, some broken edges can be detected. However, some false edges are also detected. Considering the nature of FMI images and also motivated from idea exchange with geologists, we propose a more simple and efficient way to extract shape features of rock, which includes puncture, tour and projection steps.

Puncture is a method proposed for rhyolite and crack rock. The image is scanned progressively either by row or by column, and a puncture occurs when scanning through a rhyolite or crack structure. This feature is the times that puncture happens in the whole image.

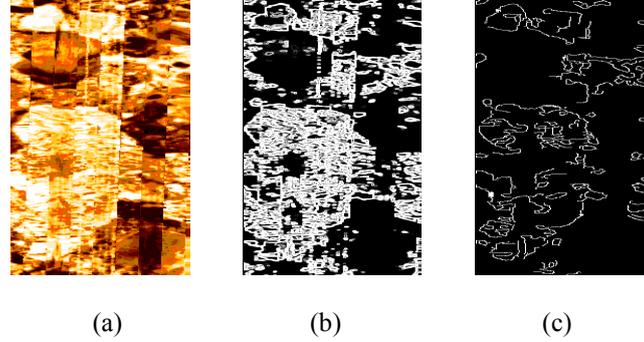


Fig. 4. Fig(a) is the original FMI image, Fig(b) is the image processed by Sobel transformation, and Fig(c) is the image processed by Canny transformation.

Tour means to scan the image progressively by row or by column. When the line enters a block, a tour starts to count the pixels until it gets out of the block. This feature is the average count of the tour, which means the total count divided by the number of blocks.

Projection is to divide the image into several blocks in proportion, project all the values of the color to the bottom, and accumulate them into one value in every block. This feature is very useful for the rock which texture is very uniform or very loose in distribution.

The features mentioned above can be calculated with different segmentation ways (by row, by column, or by block). And these shape features can be also used with color features. Consequently, all these features can be grouped into different feature vectors for rock classification.

2.3 Classifier Design and Integration

There are several commonly used classifiers: the minimum distance classifier, the nearest neighbor classifier, the k-nearest neighbor classifier, and the BP neural network classifier.

2.3.1 The Minimum Distance Classifier

The minimum distance classifier uses a base template in the feature space to represent a pattern, and the classification is based on the distance between the feature vector of the sample to be identified and this template.

If M_i is the base template of pattern class ω_i ($i = 1, 2, \dots, C$):

$$M_i = (m_{i_1}, m_{i_2}, \dots, m_{i_n})^T, i = 1, 2, \dots, C. \quad (1)$$

And if X is the feature vector of the sample to be identified:

$$X = (x_1, x_2, \dots, x_n)^T, \quad (2)$$

Here, $d(X, M_i)$ is the distance between the sample X and M_i , the base template of the pattern class ω_i , and principle is that if $d(X, M_i)$ is the smallest value in all distances, the sample belongs to pattern class ω_i . Practices proved that this is a very simple and effective method.

2.3.2 The Nearest Neighbor Classifier and the K-Nearest Neighbor Classifier

Assume that there are C pattern classes $\omega_1, \omega_2, \dots, \omega_c$, and there are N_i samples in each corresponding class, whose pattern classes are known, where $i = 1, 2, \dots, C$.

The nearest neighbor classifier uses all the samples in every pattern class as representative points, and classifies the unidentified sample X into the class whose samples are nearest to it. Therefore, the nearest neighbor classifier can partially resolve the influence caused by the differences among the sample even vectors. The discrimination function for pattern class ω_i is:

$$g_i(X) = \min_k \|X - X_i^k\|, k = 1, 2, \dots, N_i. \quad (3)$$

where the i in X_i^k means pattern class ω_i , and k means the sample k in ω_i . If Eq. (4) is satisfied, then $X \in \omega_j$.

$$g_j(X) = \min_i g_i(X), i = 1, 2, \dots, c. \quad (4)$$

The k-nearest neighbor classifier is a general version of the nearest neighbor classifier. The principle is to find k nearest samples the closest to unidentified X , and it belongs to the pattern class that most of the k samples belong to. Taking into account the efficiency decrease caused by classifiers integration and that the features selected in every layer can discriminate the rock in some extent, hence this system adopts simple and practical classifiers: the nearest neighbor classifier and the k-nearest neighbor classifier.

2.3.3 Classifier Combination

Single classifiers can be integrated into a final one. Generally, there are three methods to integrate them according to the decision-making information provided by each classifier.

The first one is decision output-oriented integration method. Although the information outputted by classifiers is very little, it is still commonly used and other forms of output can be transformed to this one. The second one is sorting output oriented integration method. This type of approaches first sorts the categories by its possibility according to the output, and then integrates them based on various strategies. The third one is the measure output-oriented method. This method exports a measure value for every category, such as probability, confidence level, or distance measure [6].

With FMI images, this rock structure recognition system is supposed to classify the rock into five types of structures: lava, tuff, tuff breccia, volcanic breccia, and ablation breccia. All these types of structures are very complex, and a single feature is not sufficient for such a complex task. Accordingly, this system needs to recognize rock structure by many effective features [7].

In this paper, for every type of rock structure, a specific feature vector is selected, and the classifiers are integrated hierarchically. Every layer uses a specific feature vector to recognize rocks of specific structure. If the rock is not recognized at the current layer, it will go on to the next layer until it is finally identified [8]. In order to get better performance, a voting mechanism is adopted based on the k-nearest neighbor classifier [9-10].

2.4 System Workflow

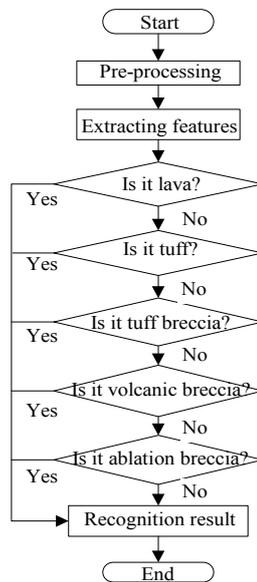


Fig. 5. System workflow

The system workflow is as shown in Fig.5, and the process is described as follows:

Step 1: Pre-process the image to be classified.

Step 2: Extract the features from the processed image.

Step 3: Recognize the image. If it is lava, go to Step 8. Else, go to Step 4.

Step 4: Recognize the image. If it is tuff, go to Step 8. Else, go to Step 5.

Step 5: Recognize the image. If it is tuff breccia, go to Step 8. Else, go to Step 6.

Step 6: Recognize the image. If it is volcanic breccia, go to Step 8. Else, go to Step 7.

Step 7: Recognize the image. If it is ablation breccia, go to Step 8. Else, classify it into some appointed type directly then go to Step 8.

Step 8: Export the result of recognition.

3 Experiments

In these experiments, we classify rock structures with some real FMI rock images obtained by the oil and gas exploration. Because of high cost of image capture and secrecy protection, the size of our experiment data is rather small (shown in Table 2). The experiments include two parts: one is for feature selection and the other is for rock classification. The results of feature selection are shown in Table 1, where we can find that different optimal feature vectors for different situations.

Table 1. The optimal feature vector

Rock Structure	Feature	Zoning Mode	Quantity of Zones
Lava	Black Vertical Puncture	Vertically	60
Tuff	Black Horizontal Puncture	Horizontally	5
Tuff Breccia	White Pixels Rate	By block	5*2
Volcanic Breccia	White Vertical Tour	Vertically	5
Ablation Breccia	Projection	Vertically	25

Then we use the above optimal features as a feature vector for rock classification. The recognition results can be seen in Table 2.

Table 2. The experimental results of this system

Rock Structure	Number of Training Set	Number of Testing Set	Classified correct	Classified wrong	Accuracy Rate %
Lava	1	34	29	5	85.3
Tuff	1	16	12	4	75.0
Tuff Breccia	1	12	10	2	83.3
Volcanic Breccia	1	16	13	3	81.3
Ablation Breccia	1	12	9	3	75.0

It can be concluded from Table 2 that with this optimal feature vector, the average accuracy rate of this system is above 80%. We can also see that, the vector partially reflects the structure characteristics. For example, the vertical puncture is corresponding to the rhyolite structure of lava. This feature is important and proves critical for recognizing lava. The accuracy rate is satisfying and can meet the demands of geologists in the oil and gas exploration. Note that, we do not compare our system with other competitive algorithms because we rarely see any intelligent rock structure recognition systems in the literatures.

In our experiments, we only use one training sample for each category. Obviously, the recognition performance can be largely improved with more training samples. As shown in Table 2, the classification accuracy of Tuff and Ablation Breccia rocks are only 75%. And another possible improvement is to investigate more effective features so as to achieve higher accuracy.

4 Conclusions

In this paper, we utilized the characteristics of rock structures from FMI images and developed an efficient intellectual rock structure recognition system using image processing and pattern recognition technologies. The recognition system is able to select useful color and shape features, and adopt multiple classifiers for the final decision of a rock structure. Experiments with real FMI images captured from the oil and gas exploration showed that our system can largely reduce the complexity and difficulty of the recognition of rock structure, and effectively raise the automatic level of exploration. Some further issues include collecting more training samples and exploiting more effective features.

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