Rock Images Analysis of FCM Clustering Algorithm Based on Weighted Color Texture Features

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Abstract. The identification and division of different components rock image are of great significance in the field of geological research. It is time-consuming and subjective to identify the rock thin sections artificially under the microscope, and the analysis results are difficult to quantify and characterize. Therefore, the use of digital image processing technology to analyse the rock image has become a hot topic in current research. It is difficult to obtain the ideal result by applying the image segmentation algorithm to the rock image for component division directly, and it can’t meet the requirements of rock image analysis. Therefore, in this paper, some weights are used to combine the color features of the rock components with the texture features, and the FCM clustering algorithm is used to achieve the division and identification of rock components. The experimental results show that the algorithm can more accurately classify sandstone particles, pores, feldspar and other minerals.

1. Introduction
The analysis of the image of the rock thin sections is the basis for the identification of the microstructure of the reservoir rock. By studying the thin sections of the rock under the microscope, not only can we understand the composition, properties and structure of the reservoir rock, but it also has very important significance and practical value for the study of the stratum and sedimentary environment of the petrolierous basin [1]. The traditional image of rock thin sections is identified manually under the microscope. It is time-consuming, laborious, subjective, and it is difficult to quantitatively characterize the results of the analysis. The identification process requires professional guidance and the development of splicing techniques. For large data volumes of full-scale rock images, manual methods have been difficult to perform fine and quantitative analysis. At this time, the analysis of rock images through image processing technology will show great potential for development in the future [2-3]. Through this technology, the shape, size, distribution, and contact with other components of various components can be achieved. Relations, etc. can be obtained directly, which is convenient for geological analysts to perform statistics and analysis and achieve quantitative characterization.

In the image of the rock thin sections, the pores are perforated with colloidal pores and present a specific color, and different minerals also exhibit a specific color. Therefore, the color characteristics should be selected as a set of main features when performing component identification. In addition, the textures of different minerals such as feldspar and quartz are also different, so the texture features of the image should also be selected as a set of main features.

For this reason, this paper firstly extracts the color features of the different color spaces in the image of the rock thin sections, performs FCM clustering comparison, selects the best color features, and then selects the best texture features by extracting different texture features for FCM clustering. Finally, an FCM clustering algorithm based on weighted color texture features was proposed and the experimental results were analysed.
2. Rock Image Features

2.1. Color Space

2.1.1. RGB color space. Usually RGB is the most commonly used color space in digital image processing and represents red, green, and blue, respectively. These three colors are also called three primary colors. Figure 2.1 shows the original image of the rock image in the RGB space and the grayscale image of the RGB components, respectively. Due to the filled red cast in the pores, the pores will show more obvious differences. So the G component and B component can be used to identify the pores. For sandstone particles, the RGB components can be clearly identified. Therefore, RGB components can be used to divide rock particles.

![Figure 2.1 RGB color space rock image](image)

2.1.2. HSV color space. HSV is a color space based on direct perceptual features. The color space is also represented by three different color components: Hue (H), Saturation (S), and Lightness (V). Figure 2.2 is a grayscale image of the rock image, HSV components in the HSV color space. Figure 2.2 (b) and (c) are the rock images under the H and S components, respectively. The H component can highlight the texture features, and the S component is more effective for the identification of mineral boundaries. Therefore, in the HSV color space, the extracted color features have a better recognition effect on the rock composition profile and texture.

![Figure 2.2 HSV color space rock image](image)

2.2. Texture Features

For different images, texture features contain richer information than geometric features and color features, and are widely used in remote sensing image processing, medical image processing, agricultural imaging, and industrial fields [4-8]. For rock section images, different rock compositions also show different texture features. For example, feldspar, quartz, pores, and sandstone particles all have specific texture features. Therefore, the extraction of texture features is also a division of rock composition. The description of texture features mainly includes statistical methods and spectral
methods. Here, we mainly introduce the gray-level co-occurrence matrix in the statistical methods used in this paper.

Gray-level co-occurrence matrix is an image processing technique that is widely used to measure image texture. It not only provides a mature and effective measurement method for texture feature analysis, but also reflects the direction of the gray level of the image, the adjacent interval and amplitude variation, etc. information. The specific formula is as follows.

\[ p(i, j, d, \theta) = \sum_{x=0}^{n} \sum_{y=0}^{m} \begin{cases} 1, & \text{if } I(x, y) = i \text{ and } I(x + d \cos \theta, y + d \sin \theta) = j \end{cases} \]  

Here, \( p(i, j, d, \theta) \) represents the relative frequency of a pixel with a gray level \( i \) in the image and a pixel \( j \) separated by a specific displacement distance \( d \) and a certain angle \( \theta \). In order to describe the texture features more intuitively using a gray-level co-occurrence matrix, some statistics are usually extracted to quantify texture features such as angular second moment, contrast, energy, and evenness.

3. Introduction to FCM Clustering Algorithm

In the FCM clustering algorithm, by introducing fuzzy division, each data element \( x_i \) is divided into clusters according to the membership degree function. That is, each data element \( x_i \) can belong to any cluster \( C_j \) by the degree of membership, but it is different. The probability of clustering \( C_j \) is different. In the clustering process, the data element \( x_i \) should be divided as much as possible into the clustering \( C_j \) with a high degree of membership, where the degree of membership is between 0 and 1. In this case, the minimization objective function of the FCM clustering algorithm is shown in Equation (2):

\[ J = \sum_{i=1}^{K} \sum_{k=1}^{N} u_{ik}^{m} \| x_k - c_i \| \]  

Among them, \( u_{ik} \) is the membership degree matrix, and \( c_i \) is the cluster center of the first \( i \) cluster. The final FCM algorithm steps are as follows:

Step1. Specify the number of clusters \( k \), and randomly initialize the membership matrix \( U \) and \( k \) cluster centers \( C_i \), define the error \( \varepsilon \);

Step2. Calculate the degree matrix \( U \) and clustering center \( C_i \);

Step3. Calculate the objective function according to equation (1). If its error is less than the given threshold \( \varepsilon \), the iteration is stopped; otherwise, it goes to Step2 to update the membership matrix \( U \) and the cluster center \( C_i \) again.

4. Experiment and Result Analysis

4.1. Selection of Color Features

In this paper, the color features of RGB and HSV color space are extracted respectively. FCM clustering is performed on different rock section images. The original image is divided by using FCM clusters with a cluster number of 3.
In order to more effectively evaluate the quality of clustering of rock image components, the partition coefficients $V_{pc}$ and the entropy division $V_{pe}$ are used as the metrics for the division of rock image components [9,10]. The larger the value of $V_{pc}$ or the smaller the value of $V_{pe}$ is, the better clustering effect will be. Specific definitions are as follows:

$$V_{pc} = \frac{1}{n} \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^2$$  \hspace{1cm} (3)$$

$$V_{pe} = -\frac{1}{n} \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij}^2 \log u_{ij})$$ \hspace{1cm} (4)$$

Table 1 is an analysis and comparison of the effectiveness of the FCM clustering of the three rock images in Figure 4.1(a1,a2,a3) using different color space features. By comparing the data in the table, it is found that the use of HSV color space for FCM clustering of rock images results in good results. Therefore, this paper finally selects the three color components of HSV color space as the color features of the clustering of rock image components.

Table 1. Clustering validity partition metrics of different color space

| Color space | Figure (a1) | Figure (a2) | Figure (a3) |
|-------------|-------------|-------------|-------------|
| RGB         | 0.6241      | 0.4124      | 0.6423      | 0.4378      | 0.6547      | 0.4144      |
| HSV         | 0.7464      | 0.3684      | 0.7145      | 0.3745      | 0.7681      | 0.3678      |

4.2. Texture Feature Selection

This paper uses the statistics in the co-occurrence matrix to perform FCM clustering. The clustering results are shown in Figure 4.2, where Figure 4.2(a1, a2, a3) is a gray scale image, Figure 4.2(b1, b2, b3), Figure 4.2(c1, c2, c3) and Figure 4.2(d1, d2, d3) are FCM clustering results of the graphs in Figure 4.2(a1, a2, a3) based on contrast, energy, and entropy in the co-occurrence matrix, respectively. There are two types of clusters. Through analysis, it can be found that in the process of clustering and dividing the rock components, the contrast can effectively represent the texture features of the rock. Therefore, this paper uses the statistical contrast in the gray level co-occurrence matrix as a texture feature to cluster the rock components.
4.3. FCM Clustering Algorithm based on Weighted Color Texture Features

In the initial clustering, the weights of the color features are increased so that they can accurately divide the components with different color features. In the later stage of clustering, the division based on color features has been stable, and it is necessary to divide the components with smaller differences in texture characteristics. Therefore, the weights of the texture features are increased so that they can be divided into elements with small differences in color features and small texture differences. In this paper, by using the weighted feature FCM algorithm, the objective function of the component division of the rock thin section image is shown in formula (5):

$$ J_X = \sum_{j=1}^{c} \sum_{i=1}^{n} \left[ \mu_j(X_i) \right]^b W_j \| X_i - m_j \|^2 $$

In the formula, $\mu_j(X_i)$ is the degree of membership of the $i$-th mode for the $j$-th cluster, $m_j$ is the $j$-th cluster center vector, and $W_j$ is the weight of the feature vector. For this algorithm, no optimization is needed and only the clustering algorithm is needed. The number of iterations can be changed accordingly. Each vector of color feature $x'_i$ and texture feature $x'_j$ respectively shares different weights. $\| X_i - m_j \|^2$ is the Euclidean distance between the $i$-th cluster center and the $j$-th data point, and $b$ is the weighted index. In this paper, the value of $b$ is 2. The constraints are as shown in equation (6):

$$ \sum_{j=1}^{c} \mu_j = 1, 0 \leq \mu_j \leq 1, \sum_{j=1}^{c} \mu_j > 0 \quad \forall i, j $$

According to Lagrange multiplication to solve the optimal value of its objective function, the update function of the membership degree matrix and the cluster center vector can be obtained, as shown in formula (7) and formula (8):

$$ \mu_j(X_i) = \frac{\sum_{j=1}^{c} \left[ \mu_j(X_i) \right]^b W_j X_i}{\sum_{j=1}^{c} \left[ \mu_j(W_j X_i) \right]^b}, \quad j = 1, 2, c. $$
Among them, $W_i=(a^i_k, \beta^i_k)$, $a^i_k$ is the shared weight of each color feature component, and $\beta^i_k$ is the shared weight of each texture feature component. In the initial clustering, the weights of the color features should be set larger, and the weights of the texture features should be set smaller so that they can accurately divide the components with different color features. In the later stage of clustering, the division based on color features has reached a stable level, and it is necessary to divide the components with small differences in texture characteristics. Therefore, the weights of texture features are increased, and the weights of color features are reduced, so that the color features can be divided. Therefore, in the clustering process, $a^i_k$ and $\beta^i_k$ are expressed as follows:

$$ a^i_k = \frac{1}{1 + e^{(k-30)}} $$

$$ \beta^i_k = 1 + e^{\frac{k}{30}} $$

In order to verify the effectiveness of the FCM clustering algorithm based on the weighted color texture features, three FCM clustering algorithms for weighted color texture features were used for the cast thin section images. The clustering results are shown in Figure 4.3. Figure 4.3(a1,a2,a3) is the original image and Figure 4.3(b1,b2,b3) is the FCM clustering result based on the weighted color texture features.

![Figure 4.3](image)

**Figure 4.3.** Comparison of FCM clustering results using weighted color texture features

Table 2 is an analysis of the effectiveness of FCM clustering of three original rock images using a weighted color and texture.

From the comprehensive table 1 and table 2, it can be seen that the use of weighted color texture features for FCM clustering of rock images results in good results, that is, based on weighted color texture features FCM clustering can improve the accuracy of the clustering of rock components.

**Table 2.** Cluster effectiveness division measure.

| Feature Clustering Algorithm                  | figure (a1) | figure (a2) | figure (a3) |
|----------------------------------------------|-------------|-------------|-------------|
| weighted color texture features FCM clustering | V_{pc} 0.7968 | V_{pe} 0.3147 | V_{pc} 0.7881 | V_{pe} 0.31462 | V_{pc} 0.8147 | V_{pe} 0.3031 |

5. Conclusion
First of all, through the experimental comparison, this paper finds that the HSV color space is more suitable for the division of the components of the rock image. Therefore, this paper finally selects the color components of the HSV color space as the color features of the cluster. Then, different statistical
statistics of image texture feature are extracted by gradation co-occurrence matrix to classify the rock image by FCM clustering. Through the experimental comparison, it is found that the contrast feature is more suitable for the composition of rock image components. In the end, by combining the color features and texture features of the extracted HSV color space, an FCM clustering algorithm based on weighted color texture features is proposed. Experiments show that the clustering result is better than the color or texture feature FCM clustering algorithm.

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7. References
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