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The Segmentation of FMI Image Layers Based on FCM Clustering and Otsu thresholding

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Abstract— A key aspect in extracting quantitative information from FMI logs is to segment the FMI image to get image of layers. In this paper, an automatic method based on FCM clustering and Otsu thresholding is introduced in order to extract quantitative information from FMI images. All pixels are clustered using FCM clustering algorithm at the first step. The second step uses KNN for other clustering. Then, uncovered columns of FMI image and image inequality are removed. Finally, the Otsu thresholding method is investigated for improving pixel-clustering step. Filed data processing examples show that sub image of layers can be accurately seprated from original FMI images.

Index Terms— FMI, Segmentation, Otsu, FCM, Thresholding, KNN, Clustering

1 Introduction

THe difficulty in carbonate reservoir evaluation come from the complexity of reservoir storage spaces (such as pores, vugs, fractures and their combination) and thir heterogeneity. Because of fractures, the validity of the reservoir is not easily identified by conventional log. The imaging log provides a new means for such a complex reservoir evaluation. FMI (Full Micro-resistivity Imager) provides borehole wall resistivity imaging. The FMI tool is made of eight electrode pads with 24 button electrodes on each pad. The FMI tool sample interval in depth and well circumference is 0.1 inch. The tool covers approximately 80% of the borehole wall in an 8.5 inch hole. The FMI image clearly shows the geological phenomena around the borehole wall [1].

In order to extract qualitative information from FMI, a basic step is used to segment the FMI image to get sub-image of layers. Then, the segmented images are analyzed and processed to extract relevant information. The segmentation result directly affects the accuracy of parameter calculation [2].

A number of image segmental algorithms have been developed in the literature. They can be rouly grouped in two categories: area description-based algorits and edge detection-based methods [3].

In this paper, we present a segmentation method based on Fuzzy C-mean algorithm and Otsu thresholding method. The first step classify pixel of each row of FMI image using fuzzy C-mean algorithm. At the second step, we use k-nearst neighbor for classifying. Then we remove uncovered columns and remove image inequalities. At the end we use Otsu thresholding method.

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2 Proposed Method

The complete block diagram representation of the proposed method is shown in Figure 1. After inputting a FMI image, we select intensity values of red, green, blue and equivalent gray level of each pixel as features. Then we normalize these features for each row of image. At section 2.1 we illustrate the normalization method. After this step, we cluster pixel of FMI image using fuzzy c-mean (FCM). Feature selection, feature normalization and FCM have been performed to last row of FMI image.

Then k–nearest neighbor algorithm (KNN) has been called on each row of image. KNN has been explained in section 2.3. Then uncovered columns have been removed (section 2.4). We illustrate removing image inequality method in section 2.5. In section 2.6 we explain Otsu thresholding method.

2.1 Normalization

As leave-one-out scheme is used, for each feature in the training samples the feature normalization is adapted based on the following scheme:

$$f_i = \frac{f_i - \mu_i}{\sigma_i} \quad (1)$$

Where f_i, μ_i and σ_i are respectively i-th feature, mean and standard deviation of i-th feature [4].

2.2 Fuzzy C-Means Cluster

Feature selection and feature normalizationrun on each row of FMI image, then fuzzy c-means (FCM) executed.This process runs until arrive to last row of FMI image (Fig 1).

FCM is a method of clustering which allows one piece of data to belong to two or more clusters. This method is frequently used in pattern recognition [5]. It is based on minimization of the objective function:

$$J_q(U,V)=\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^q d^2(x_k,v_i) \quad (2)$$

where $X=\{x_1, x_2,\ldots, x_n\}$, n is the number of data items, c is the number of clusters with $2 \le c \le n$, u_{ik} is the degree of membership of x_k in the i-th cluster, q is a weighting exponent on each fuzzy membership, v_i is the prototype of the center of cluster i, $d^2(x_k, v_i)$ is a distance measure between x_k object and cluster centre v_i. A solution of the object function can be obtained via an iterative process, which is carried as follows:

1) Set value for c, q and ε.
2) Initialize the fuzzy partition matrix U.
3) Set the loop counter $b = 0$.
4) Calculate the c cluster centers $\{v_i^{(b)}\}$ with $U^{(b)}$:

$$v_i^{(b)}=\frac{\sum_{k=1}^{n}(u_{ik}^{b})^q x_k}{\sum_{k=1}^{n}(u_{ik}^{(b)})^q} \quad (3)$$

5) Calculate the membershi $U^{(b+1)}$. For $k=1$ to n,calculate the following

$$I_k=\{i \mid 1\le i\le c,\ d_{ik}=\|x_k - v_i\|=0\}, \quad (4)$$

$$\tilde{I}_k=\{1,2,\ldots,c\}-I_k \quad (5)$$

For the *k-th* column of the matrix, compute new membership values:
If $I_k = \varphi$, then

$$u_{ik}^{(b-1)}=\frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/(q-1)}} \quad (6)$$

Else $u_{ik}^{(b-1)} = 0$ for all I $\in I_k$ and

$$\sum_{i\in I_k}u_{ik}^{(b-1)}=1 \text{ next k} \quad (7)$$

6) If $\|U(b)-U(b-1)\|<\varepsilon$, stop; otherwise, set $b=b+1$ and go to step 4 [6].

2.3 K-Nearest Neighbor

K-nearest neighbor (k-NN) is a supervised learning algorithm by classifying the new instances query based on majority of k-nearest neighbor category. Minimum distance between query instance and the training samples is calculated to determine the k-NN category. The k-NN prediction of the query instance is determined based on majority voting of the nearest neighbor category. Since query instance (test image pixel) will compare against all cluster [7].

In this works, for each test pixel image (to be predicted), minimum distance from the test pixel image to the training set is calculated to locate the k-NN category of the training data set. Euclidean Distance measure is used to calculate how close each member of the training set is to the test class that is being examined. Euclidean Distance measuring:

$$d_E(x,y)=\sum_{i=1}^{N}\sqrt{x_i^2-y_i^2} \quad (8)$$

From this k-NN category, class label of the test pixel image is determined by applying majority voting [8].

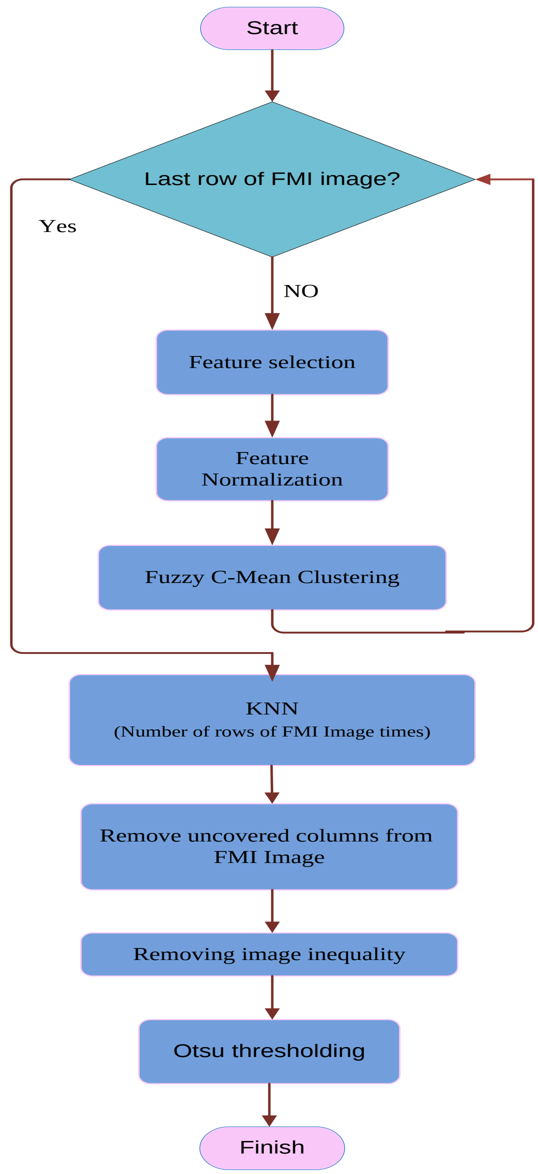

Fig. 1. Block diagram of proposed system

2.4 Removing Uncovered Columns

At this step, we assume the columns that all pixels categorized to same class, are uncovered columns of FMI image (20% of FMI image). Therefore these columns remove.

2.5 Removing Image Inequality

In proposed system, a nonlinear filter is used that remove non-edge surface roughness image and keep edges FMI images. First, for each pixel we calculated eight derivatives in all direction. Then the combination of the eight derivatives added to pixels value. Figure 2 shows the pixel (n, m) and its eight neighbors. Equation (9) computed the derivative of pixel neighbors. In this equation, I_i represents the gray level of i-th neighbors of pixel (n, m). After calculating derivatives in all direction, these values multiplied by the coefficient δ and added to pixel value (equation (10)). As shown in equation (9), this filter has three parameters (K, α and δ). Their value in this study is considered 0.02, 2.5 and 1.25 respectively.

I_2	I_3	I_4
I_1	$I_{n,m}$	I_5
I_8	I_7	I_6

Figure 2: pixel (n, m) and 3×3 neighborhood

$$\delta_i = I_i - I(n,m) \tag{9}$$

$$I(n,m) = I(n,m) + \delta\{\frac{\delta_1}{1+\left|\frac{\delta_1}{K}\right|^{\alpha}} + \ldots + \frac{\delta_8}{1+\left|\frac{\delta_8}{K}\right|^{\alpha}}\} \tag{10}$$

As noted above, this filter removes non-edge surface roughness and keeps edges in FMI images. Based on above relationships, if derived value in the edge pixel be larger than parameter K then the absolute operand is greater than 1. After ^, obtained a large value and changed a little on the intensity of edge pixel. Therefore the filter has no effect on the edge pixels. Furthermore, for non-edge pixels, the absolute value is smaller than 1 and can skip it. Thus equation (10) in limit case is Laplace for non-edge pixels and acts as a smoothing filter. In addition, we can use this nonlinear filter much time [8]. Figure 7 shows multiple repeated of this filter and in each stage, the image obtained is displayed [9].

2.6 Otsu Method

In this section, we use Otsu method [10] as follows. Assuming an image is represented in L gray levels [0, 1, …L-1]. The number of pixels at level i is denoted by n_i, and the total number of pixels is denoted by $N = n_1 + n_2 + \ldots + n_L$. The probability of gray level i was denoted by

$$p_i = ni \; / N \, , pi \geq 0, \sum_0^{L-1} p_i = 1 \tag{11}$$

In bi-level thresholding method, pixels divided into two classes C_1 with gray levels [0, 1, …, t] and C_2 with gray levels [t+1, …, L-1] by the threshold t. The gray level probability distributions for two classes are

$$w_1 = \Pr(C_1) = \sum_{i=0}^{t} p_i \tag{12}$$

$$w_2 = \Pr(C_2) = \sum_{i=t+1}^{L-1} p_i \tag{13}$$

The means of class C_1 and C_2 are

$$u_1 = \sum_{i=0}^{t} ip_i / w_1 \tag{14}$$

$$u_2 = \sum_{i=t+1}^{L-1} ip_i / w_2 \tag{15}$$

The total mean of gray levels is denoted by u_T

$$u_T = w_1 u_1 + w_2 u_2 \tag{16}$$

The class variances are

$$\sigma_1^2 = \sum_{i=0}^{t} (i - u_1)^2 \, p_i / w_1 \tag{17}$$

$$\sigma_2^2 = \sum_{i=t+1}^{L-1} (i - u_2)^2 \, p_i / w_2 \tag{18}$$

The within -class variance is

$$\sigma_w^2 = \sum_{k=1}^{M} w_k \sigma_k^2 \tag{19}$$

The between-class variance is

$$\sigma_B^2 = w_1 \left(u_1 - u_T\right)^2 + w_2 \left(u_2 - u_T\right)^2 \tag{20}$$

The total variance of gray levels is

$$\sigma_T^2 = \sigma_w^2 + \sigma_B^2 \tag{21}$$

Otsu method chooses the optimal threshold t by maximizing the between-class variance, which is equivalent to minimizing the within-class variance, since the total variance (the sum of the within-class variance and the between-class variance) is constant for different partitions [11].

$$t = \arg\{\max_{0 \le t \le L-1} \{\sigma_B^2(t)\}\} = \arg\{\min_{0 \le t \le L-1} \{\sigma_w^2(t)\}\} \tag{22}$$

Otsu method can be extended to multilevel thresholding method. Assuming that there are M-1 thresholds $[t_1, t_2, \ldots, t_{M-1}]$ that divide the pixels in the image to M classes $\{C_1, C_2, \ldots, C_M\}$

$$\begin{aligned} \{t_1, t_2, \ldots, t_{M-1}\} &= \arg\{\max_{0 \le t \le L-1} \{\sigma_B^2(t_1, t_2, \ldots, t_{M-1})\}\} \\ &= \arg\{\min_{0 \le t \le L-1} \{\sigma_W^2(t_1, t_2, \ldots, t_{M-1})\}\} \end{aligned} \tag{23}$$

Where

$$w_j = \sum_{i=t_{j-1}+1}^{t_j} p_i \tag{24}$$

$$u_j = \sum_{i=t_{j-1}+1}^{t_j} ip_i / w_j \tag{25}$$

$$\sigma_j^2 = \sum_{i=t_{j-1}+1}^{t_j} (i - u_j)^2 p_i / w_j \tag{26}$$

$$\sigma_B^2 = \sum_{j=1}^{M} w_j (u_j - u_T)^2 \tag{27}$$

$$\sigma_W^2 = \sum_{j=1}^{M} w_j \sigma_j^2 \tag{28}$$

3 Experiments and Results

Original FMI image is represented in Fig. 3. The output of all steps of proposed system has been shown in Fig. 4 to Fig. 8. Fig. 4 is pixels clustering after FCM algorithm. The result of KNN algorithm is shown in Fig. 5. Removeing of uncovered columns of FMI image is determind in Fig. 6. Fig. 7 shows Output image after Removing Image Inequality. Finally, Fig. 8 shows the resulting segmented image after Otsu thresholding method.

4 Conclusion

We have proposed a segmentation method based on FCM clustering and Otsu thresholding. The field data processing examples show that sub image of layers can be accurately seprated from original FMI images.

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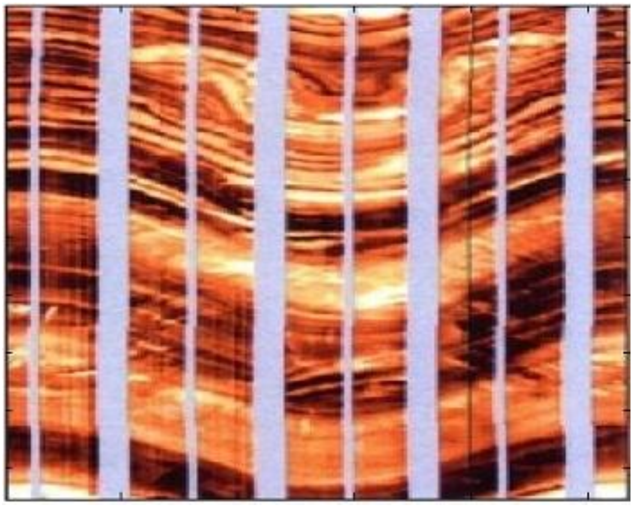

Fig. 3. Original FMI image.

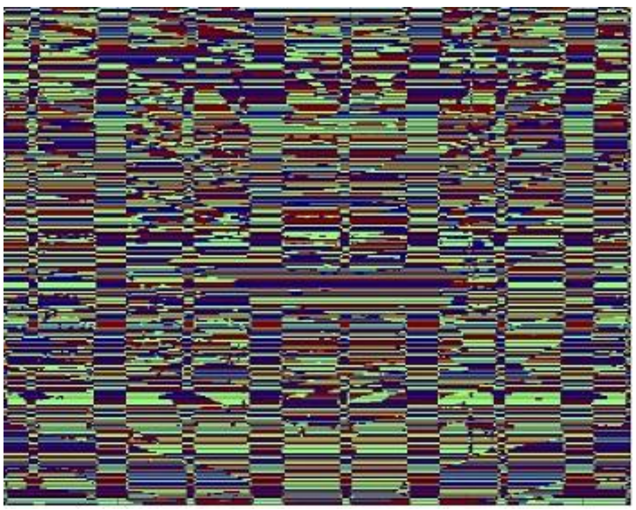

Fig. 4. Pixels after FCM clustering algorithm.

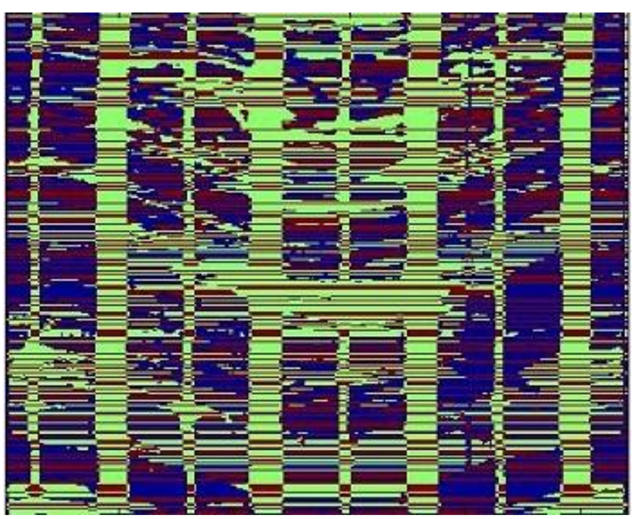

Fig. 5. Pixels after KNN algorithm.

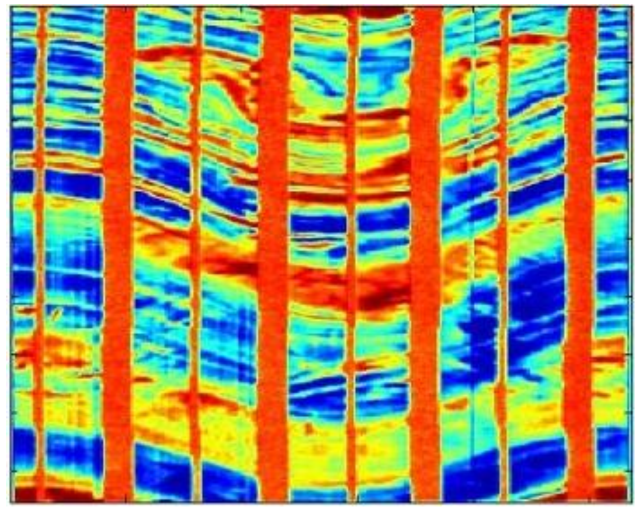

Fig. 6. The uncovered columns of FMI image are determind.

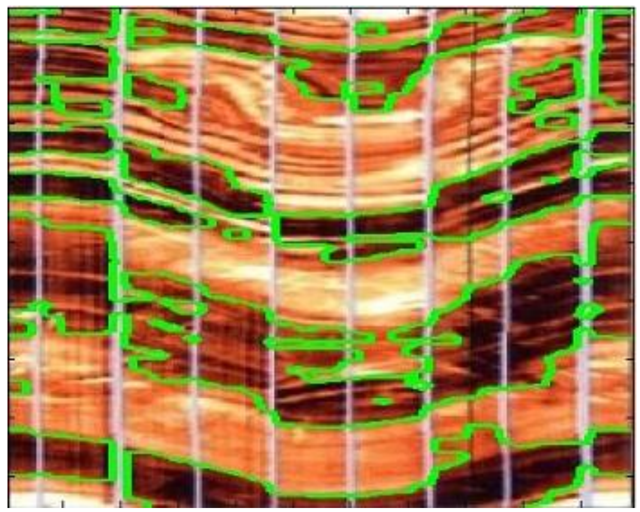

Fig. 7. Output image after Removing Image Inequality.

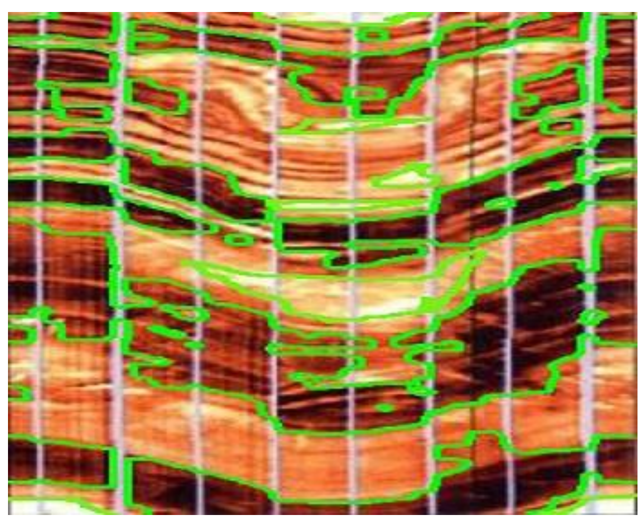

Fig. 8. Final output after Otsu thresholding method.