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Automatic detection of formations using images of oil well drilling cuttings

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ABSTRACT

In oil well drilling process, a perennial issue is formations detection particularly in passing through high and low pressure formations. However, automatic classification of keybeds in the Gachsaran and Asmari formations by applying drill cutting images can help in decision-making, especially in oil wells of Iran, about mud weight and casing design for oil well drilling process. First, this study focuses on color analysis and fuzzy *c*-mean clustering to extract relevant features from images of the drill cuttings. Furthermore, a support vector machine and different kernel functions are utilized to classify the samples into different keybeds. Second, due to changing color of drilling cutting in each well, this study proposes texture analysis for keybeds classification. In this method, a co-occurrence matrix and features of energy, homogeneity, entropy and brightness are applied as feature vectors and classification is done by using the support vector machine too. This study, moreover, introduces the accuracy and response speed of the above techniques. To sum up, the results show that this method can be used to detect different formations (particularly between Gachsaran and Asmari) by approximately 95% accuracy.

1. Introduction

Oil well drilling is a time consuming, complicated and costly process, so that Increasing the speed and safety of this process can benefit experts to find discrepancy in different formations easily (Zhou et al., 1998; Qin and Zhang, 2004). Nevertheless, one the main issue for oil well drilling, especial Iranian oil wells, is the passing from low-to-high pressure formations and vice versa, so to resolve it Geologists have to stay on the site and study drill cuttings features after extraction to identify the type of formations. In Iranian oil wells based on their geological structure, a critical interface is Gachsaran-Asmari formation contact. Moreover, the low pressure of Gachsaran cap rock is roughly 4000 PSI although the Asmari formation pressure is less than 800 PSI. Both changing the casings at the point of contact and using low mud pressure are important factors should be taken into account when the process meets this boundary.

Nowadays, intelligent processing techniques have been improved significantly to solve geologic problems. During the drilling process, various methods have been introduced to verify the type of formations and lithology (Qi et al., 2009) and also some researchers have monitored the stages of drilling (Frantiek et al., 2000; Hayajneh, 2007; Mcleod and Minarovic, 1994). Marana et al. (2009), however, designed a system to estimate the collapse of well bore-hole walls and also they captured images of drilling cuttings on a shale shaker as a system model to gather data for their research.

To classify oil wells, one common method is to apply mud-logging data that Serapiao et al. (2006) analyzed them and classified several stages of an oil well by applying pattern recognition techniques. Considering the significant volume of mud-logging data, they used a support vector machine (SVM) to identify formations during drilling. In the other cases, Coelho et al. (2005), Fonseca et al. (2006), and Yilmaz et al. (2002) successfully used neural networks to monitor drilling activities. However, Khorram et al. (2012) recently identified and classified different sedimentary rocks by extracting texture features successfully besides applying support vector machine to classify sedimentary rocks. Although lots of researches have been conducted successfully on different kinds of rocks by using novel image processing approaches, they have not particularly focused on formations detection and classification. Because there are not enough researches in this topic, this paper presents the methods to assist geologists to make decision on formations.

The present study applies texture analysis and co-occurrence matrix calculations to extract of the features of energy,

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homogeneity, contrast and correlation. In addition, SVM multi-classes are employed to classify the keybeds of the Gachsaran and upper Asmari formations. The pixels of each image, furthermore, are divided into two clusters by color analysis and fuzzy *c*-mean clustering to extract mean and covariance matrices for classification by using SVM. The performance and speed of these two methods are compared and it acknowledges that the results of these two classifications are satisfactory.

2. Methods

2.1. Co-occurrence matrix

There are plenty of methods for extricating texture from images, including wavelet analysis, Gabor filters, texture energy laws, and a gray level co-occurrence matrix. Admittedly, the gray level co-occurrence matrix (GLCM) is one of the main efficient methods of texture analysis (Maillard, 2003; Jian-hui and Yu-jing, 2007; Hu et al., 2008). In GLCM, furthermore, the co-occurrence matrix is defined as (1):

$$p(i,j,\delta,\theta)=\{[(x,y),(x+\Delta x,y+\Delta y)]|f(x,y)=i;f(x+\Delta x,y+\Delta y)=j\};$$
$$x=0,1,2,\ldots,X_x-1;\quad y=0,1,2,\ldots,Y_y-1,\theta\in\{0^\circ,45^\circ,90^\circ,135^\circ\} \tag{1}$$

where X and Y are the positions of pixels in the image x_x is the number of rows, and y_y is the number of columns. The range of δ varies from 1 up to the image size.

Haralick et al. (1973) extracted 14 statistical features; however, Ohanian and Dubes (1992) believed that four of them are more effective than the others: contrast, correlation, energy, and homogeneity, which are defined as:

$$Con=\sum_{i,j}(i-j)^2p(i,j) \tag{2}$$

$$COR=\frac{\left[\sum_i\sum_j((ij)p(i,j))-\mu_x\mu_y\right]}{\sigma_x\sigma_y} \tag{3}$$

$$\mathrm{ASM}=\sum_i\sum_j p(i,j)^2 \tag{4}$$

$$HOM=\sum_{i,j=0}^{N-1}\frac{p(i,j)}{1+(i-j)^2} \tag{5}$$

The present study extracts the feature vector from these 4 features in the 4 directions of $\theta\in$ (0°, 45°, 90°, 135°) and produced 16 dimensional axes.

2.2. Fuzzy c-mean clustering

At first, Fuzzy *c*-mean clustering (FCM) was expressed by Dunn (1973) then developed by Bezdek (1981). It, moreover, currently has numerous applications for statistic verification of algorithms. The algorithm is based on minimizing the fuzzy function (6):

$$J_m(U,V)=\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m d_{ik}{}^2(x_k,v_i),\quad U=\{u_{ik}\}\in R^\infty,\quad V=\{v_1,v_2,\ldots,v_c\} \tag{6}$$

In this algorithm, data collections are divided into C clusters by $x=\{x_1,x_2,\ldots,x_n\}$. The membership of a piece of data has a rate x_k in class I that is defined by u_{ik} and v is an axis containing the cluster center (Wang et al., 2010). Bezdek and Pal (1995) have proved that the best variation range for m is [1.5, 2.5] and $m=2$ is usually the best choice. To minimize function 6, four steps are required:

1. Assigning a random value to the center of a cluster.
2. Calculating the matrix of the membership rate of each piece of data is as (7):

$$u_{i,k}=\begin{cases}\left[\sum_{j=1}^{c}\left(\frac{d_{ik}(x_k,v_i)^{2/(m-1)}}{d_{jk}(x_k,v_j)^{2/(m-1)}}\right)\right]^{-1} & k=1,2,\ldots,n,\ \|x_k-v_j\|\neq 0\\ 1 & \|x_k-v_j\|=0(k=j)\\ 0 & \|x_k-v_j\|=0(k\neq j)\end{cases} \tag{7}$$

3. Updating the cluster center by:

$$v_i=\frac{\sum_{k=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{n}(u_{ik})^m},\quad i=1,2,\ldots,c \tag{8}$$

   and calculation as $J_m(U,V)$.
4. Defining criteria of $\|J_m^{(k+1)}-J_m^k\|\leq\varepsilon$ as conditions for stoppage of the algorithm; otherwise return to step two and change k to $k+1$.

Convergence and stoppage of the algorithm allow the calculation of the center of each class and the dependency rate of each sample to each class. To use this algorithm, the maximum dependency rate of each group is usually expressed the dependence of that member on the group.

2.3. Support vector machine

The SVM is designed to separate two classes, but can be extended for separation multiple classes (Schölkopf, 1999). Linear SVMs, particularly, have become popular for learning problems with high dimensional data (such as image or text) and large number of training examples. SVM theory designs a hyperplane with a normal vector $w$and the space of origin b. The discriminator function $F(x)$ is defined as:

$$F(x)=w\times x+b \tag{9}$$

The learning data (n) contains learning samples defined by $(x_1,y_1),\ldots,(x_n,y_n)\in R^N\times\{\pm 1\}$ for classification by the SVM. When the learning data can be discriminated into a linear pattern, the discriminator plane of hyperplane $F(x)$ can be discerned as:

$$y_iF(x_i)\geq 1,\quad i=1,\ldots,n \tag{10}$$

To solve this problem, α_i is defined as a Lagrange multiplier (Christiani and Shawe-Taylor (2000):

$$L(w,b,\alpha)=\frac{1}{2}||w||^2-\sum_{i=1}^{n}\alpha_i y_i(w\bullet x_i+b)-1),$$
$$\alpha_i\geq 0,\quad i=0,\ldots,n \tag{11}$$

The problem is solved for w and b to maximize α_i in (11); α_i belongs only to a series of non-zero learning data where learning samples of $\alpha_i\neq 0$ are the support vector. These learning samples have a minimum distance to the discriminator plane. Editing Eq. (11) obtains Eq. (12) (Ravikumar et al., 2010):

$$\max L(w,b,\alpha)=\sum_i\alpha_i-\frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_{j(x_i^T x_j)},\ \sum_i\alpha_i y_i=0,\alpha_i\geq 0\forall i \tag{12}$$