Methods and Algorithms of Cluster Analysis in the Mining Industry

Solution of Tasks for Mineral Rocks Recognition

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Abstract: It is described the algorithm for automatic segmentation of colour images of ores, using the methods of cluster analysis. There are some examples illustrated using of the algorithm in the solving of mineral rock recognition problems. Results of studies are demonstrated different colour spaces by k-means clustering. It was supposed the technique of pre- computing the values of the centroids. There is formulas translation metrics colour space HSV. The effectiveness of the proposed method lies in the automatic identification of interest objects on the total image, tuning parameters of the algorithm is a number that indicates the amount allocated to the segments. This paper contains short description of cluster analysis algorithm for the mineral rock recognition in the mining industry.

1 INTRODUCTION

Petrography is the science studies the material composition of the rocks. Unlike minerals, rocks are aggregates composed of different minerals (Harvey and Tracy, 1995).

Knowledge of the modal composition of the rock or ore is very important for solving the mineralogical and technological issues (Baklanova, 2013).

Today, in the analysis of rocks are widely used both traditional and modern mineralogical and analytical techniques: optical and electron microscopy, X-ray diffraction, electron microprobe, and elemental analyses, and the methods are widely involved studying the physical properties of minerals (Clarke and Eberhardt, 2002).

Minerals called homogeneous in composition and structure of the rocks and ores. They are natural chemical compounds resulting from various geological processes. Historically, the minerals initially determined by color and shape (Chris, 2002).

Reliability of research depends on several factors (Farndon, 2006):

- Natural mineral color variations;
- Structure errors in measurement technology of color parameters of the mineral;
- Errors in measurement and control standards and control techniques for measuring color diagnostic indicators;
- Uncertainty normative values in the system of quantifying color diagnostic indicators.

Accuracy of control, diagnosis and decision-making system in the petrography analysis can be enhanced by the presence of a database with information on the location of the test sample rocks, geological landscapes and related rocks. For example, gold often occurs with milk quartz. Minerals occur together, called associating minerals (Shaffer, Herbert and Raymond, 2001).

Using cluster analysis techniques can significantly improve the accuracy of not only the process of monitoring and diagnosing, but also to quantify the mineral content of the sample rock (Isayenko, Borishanskaya and Afanasyev, 1986).

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2 MATERIALS AND METHODS

2.1 Theoretical Background

Clustering - is the automatic partitioning of a set of elements into groups according to their similarity. Elements of the set can be anything, for example, data or characteristics vectors. Themselves groups are also called clusters (Tryon, 1939).

In our case, using algorithms of cluster analysis will be the identification of ore minerals by color and texture characteristics of color-coded minerals identified in images taken in reflected light using a microscope (Panteleev, Egorova and Klykova, 2005).

The proposed method consists in measuring the intensity of the three spectral components of the reflected light (red, green, blue) in each pixel of the investigated surface (frame) of a rock sample. Rock sample is subjected to a pre-treatment and preparation of the surface to be scanned, for example in the form of ore.

In most cases preparation of the samples represented by the following general form:

- Cutting of the sample;
- Grinding;
- Polishing.

After the sample has been prepared, it is analysed with a microscope. A laboratory microscopic picture reflects the structural features of objects (color, texture, space and so on), determines the results of mineralogical analysis.

Theoretically possibility to determine the mineral ore targets on the microscopic image substantiated by author M.P. Isayenko ((Isayenko, Borishanskaya and Afanasyev, 1986).

In this paper it describes the algorithm for automatic segmentation of color images of rocks, using the methods of cluster analysis. There are results of studies different color spaces for clustering k-means (Huang, 1998).

In general, the K-means method segments the image on K different clusters (areas) located far away from each other based on certain criteria (Odell and Duran, 1974).

As such a characteristic can be selected color (the values of all three components simultaneously RGB) color and geometric distance at the same time, etc. By default, the implementation of this method is applied to states Euclidean metric (Mandel, 1988).

Segmentation method "K- means" is implemented through a two-step algorithm that minimizes the sum of distances "point-to- centroid" obtained by summing over all K clusters. Another words, the purpose of the algorithm is to minimize variability within clusters and maximize variability between clusters (Ryzin, 1977).

Algorithm starts with a randomly selected cluster centroid position, and then changes the ownership of points (objects) to clusters, i.e. point moves from one cluster to another in order to get the most significant result.

During the first phase on each iteration all points are rearranged so that they are positioned as close as possible to their centroids, and then converted coordinates centroids of each cluster. This part of the algorithm allows to find quickly, but only an approximately a solution to the problem of segmentation, which is the starting point for the second phase.

During the second stage of the algorithm points are individually subjected to rearrangement in case it reduces the sum of the distances, and the coordinates of the centroids clusters after rearrangement recalculated for each point. Each iteration during the second stage consists of only a single pass through all the points.

After completion of the segmentation algorithm described program may provide additional information such as:

- Sum of distances "point-to-centroid";
- Coordinates of centroid as well as some other data.

Algorithm K-method can converge to a local optimum, when the separation points move any point to another cluster increases the resultant sum of the distances. This problem can be solved only by a reasonable (successful) choice of initial points (Odell and Duran, 1974).

2.2 Color Image Segmentation Algorithms

Segmentation is the process of dividing an image into regions. Color segmentation in the vector space RGB is as follows. Suppose that our goal is to allocate objects in the image RGB, the color of which lies within a certain range. Having some representative sample vectors, we are interested in having the color; we obtain an estimate of the "average" of color you want to select. Let this average color RGB denotes a column vector of T. The problem of segmentation is to classify each pixel RGB image and determine it belongs selected "average" color-class or not. It is necessary to have some measure of similarity of colors to implement such a comparison (Martin, Fowlkes and Malik, 2004).

The simplest such measure can serve as the Euclidean distance. Let z - an arbitrary point in RGB. We say that a point z is similar in color to m, if the distance between these points does not exceed a certain threshold T. The Euclidean distance between z and m is calculated by the formula:

$$D(z,m) = \|z-m\| = \left[(z-m)^T (z-m)\right]^{\frac{1}{2}} = \left[(z_R - m_R)^2 + (z_G - m_G)^2 + (z_B - m_B)^2\right]^{\frac{1}{2}}, \quad (1)$$

where || • || denotes the norm of the argument, and subscripts R, G and B are used to indicate the RGB components of the vectors z and m. The locus of points for which $D(z,m) \le T$ is a sphere of radius T. By definition, a point lying inside the ball or on the spherical surface, the color matches a specified criteria, and points lying outside of the ball and its boundary sphere - not satisfy.

If you assign the two respective sets of image values, for example, 1 (white) and 0 (black), you get a binary image, which is the result of image segmentation. Useful generalization of the Euclidean distance is the distance defined by the expression:

$$D(z,m) = \left[(z-m)^T (z-m)\right]^{\frac{1}{2}}, \quad (2)$$

where C is the covariance matrix representative sample vectors with the color to be segmented . This distance is called the Mahalanobis distance. The locus of points for which $D(z,m) \le T$ is a three-dimensional ellipsoid has the following important property: the direction of its principal axes coincide with the directions of the largest variance of the data sample. If the covariance matrix C is the identity, the Mahalanobis distance is the usual Euclidean distance. Segmentation procedure is the same as described in the preceding paragraph, only the data is now surrounded not ball but ellipsoid.

2.3 Implementation of Cluster Analysis Algorithm for Pattern Recognition Tasks of Mineral Ore

It is considered the problem of cluster analysis to segment micro-images in mineralogy. In this case, the cluster is uniform in color-luminance characteristics region (segment) if digital image. And according to the specifics of digital images mineral rocks might be in the same cluster multiple segments, and research method determines homogeneity of individual clusters.

Due to two factors it was reasonable to use cluster analysis for the problem of segmentation: there is only one tuning parameter k – a number of clusters that you want to highlight, and the sets of color-brightness characteristics associated with different types of segments analysed image are compact (Privalov and Butenko, 2007).

Any digital image has finite limits of size. Because of this image can be considered as the matrix I, which has the dimension [MxN], where M - the number of pixels horizontally and N - is the number of vertical pixels.

Each pixel with coordinates (x, y) corresponds to a feature vector $P_{x,y}$ .in form (3)

$$P_{x,y} = \left\{P^1_{x,y}, P^2_{x,y}, \ldots, P^n_{x,y}\right\}, \quad (3)$$

where: $P^n \in \left[P^n_{\min}, P^n_{\max}\right]$ – limits of characteristics changes.

For color model RGB, n=3, and $P = \left\{R_{x,y}, G_{x,y}, B_{x,y}\right\}$, where $R_{x,y}, G_{x,y}, B_{x,y}$ - brightness of the red component of the pixel, the green, and blue at point (x,y), $P^n \in [0,255]$. This allows to say that the image is the set of vectors (observations) $P_{x,y}$ in n- dimensional space P, uniquely describes the color - luminance pattern ($x = 0,\ldots,M-1$, $y = 0,\ldots,N-1$) shown in digital image. As components of $P_{x,y}$ can also act describing the neighbourhood of a given size parameters for the pixel (x, y). These parameters include the variance, average, maximum or minimum brightness, calculated from the neighbourhood, etc. Based on the characteristics of the particular image heuristically determined the number of components and composition, as well as the radius of the neighbourhood (Tremeau and Borel, 1997).

The purpose of cluster analysis - to implement such a partition of the n-dimensional feature space for k-clusters, in which the length between centroids of the resulting clusters would be greatest, it is shown in the expression (4).

$$d_{i,j} \to \max, \quad (4)$$

where $d_{i,j}$ - distance between centroids for i-th and j-th cluster, $i = 0,\ldots,k$, $j = 0,\ldots,k$.

In this case, the most appropriate method of solving the problem of clustering is classic algorithm of unsupervised learning - a method of k-means (k-means method). Clustering incrementally in this case is as follows:

Step 1. Specifies the number of clusters K, you want to find.

Step 2. It is randomly selected K vectors P’ from the set of vectors in selected space P. These K vectors are centroids of the clusters on the initial calculation stage.

Step 3. Calculate the distance from each vector space used to each of the obtained centroids in step 2. It can be used metric (5)-(6) to determine the distance.

$$D_{(x,y)k} = \sqrt{\sum_{p=1}^{n}(P_{x,y}^{p} - P_{k}^{p})^{2}} \quad , \tag{5}$$

$$D_{(x,y)k} = \sum_{p=1}^{n}\left|P_{x,y}^{p} - P_{k}^{p}\right| \quad , \tag{6}$$

where: (x,y)- coordinates of the observation,

$k \in [1,K]$ – cluster index,

n - dimensionality of the used feature space,

$p \in [1,n]$ - index of the feature observations.

Step 4. Determine the centroid of the cluster to which the distance from the observation is smallest. This cluster matched the observation.

Step 5. Goes through all available vectors and then recalculate centroids for each resulting cluster according (7).

$$P'^{n}_{(x,y)k} = \frac{1}{S(k)}\sum_{s=1}^{S(k)} P^{n}_{(x,y)s} \tag{7}$$

where: k – cluster index,

S(k) - number of observations related to the cluster index k,

s – indexes of the observations,

$P_{k}^{'n}$ – new value n-th feature of centroid cluster k.

Step 6. Steps 3-5 iterative process stops when the process centroids’ changes stops or centroids will be fluctuate around some stable values. If the step of centroids change reached a predetermined value also possible to stop iterations.

The disadvantage of the method of random selection of the centroids is that the segmentation result does not possess an important property of repeatability.

This fact makes it unusable k-means algorithm in its classical form for subsequent classification of the selected objects, and therefore requires increasing its stability in solving the problem of image segmentation of mineral rocks samples.

Solutions to problems of inadequate segmentation include the following - the development of methods for obtaining initial values of the centroids and selecting a set of parameters, forming a vector of observations, most fully satisfying description of the characteristics shared segments.

2.4 Selection of the Feature Space

Feature vector for image segmentation by clustering method is chosen heuristically. Texture in images of samples mineral rock is not critical and noted that a significant difference is observed for color-brightness characteristics. Consequently, as the feature space for solving the problem of image segmentation is one of the existing color spaces is quite suitable (Gonsales and Woods, 2011).

It is important to choose a color space with minimal correlation between describing its components. It was selected HSV color space based on the study of the logical and mathematical representation of color models, defined by (8-10).

$$H = \begin{cases} \dfrac{60(G-B)}{\max(R,G,B)-\min(R,G,B)}, if\ R = \max(R,G,B \\ 120 + \dfrac{60(B-R)}{\max(R,G,B)-\min(R,G,B)}, if\ G = \max(R,C \\ 240 + \dfrac{60(R-G)}{\max(R,G,B)-\min(R,G,B)}, if\ B = \max(R,C \end{cases} \tag{8}$$

$$S = \frac{\max(R,G,B)-\min(R,G,B)}{\max(R,G,B)} \tag{9}$$

$$V = \max(R,G,B) \tag{10}$$

where: R,G,B – the brightness of red, green and blue component, respectively, for the RGB color space,

H - color, represented by the angle between the vector of pure red and current, the range of values from 0 to 2 π,

S – saturation, the range of values from 0 to 1,

V – brightness, takes a value from 0 to 1.

HSV space is visually represented in the form of a cylindrical coordinate system. It is showed in Fig.1.

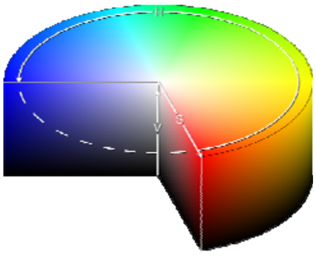


Figure 1: HSV space visually representation.

Figure 2 shows classically cylindrical coordinate system representation.

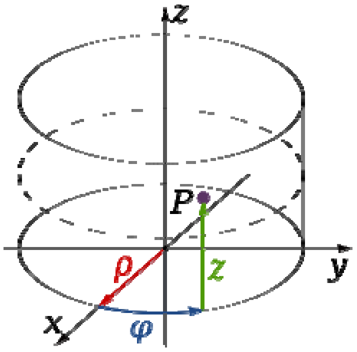


Figure 2: Classic cylindrical coordinate system representation.

On Figure 2, ρ - the distance from the point to the origin of rotation, φ - angular coordinate, z - the distance from the plane of the base to the point.

Thus, these are the coordinates of point P(ρ,φ,z).

Coordinates of this same point at the transition to the Cartesian coordinate system can be written as the following expressions (11).

$$\begin{cases} x = p \cdot \cos\varphi \\ y = -p \cdot \sin\varphi \\ z = z \end{cases} \qquad (11)$$

Direct calculations in the cylindrical coordinate system are more complicated than those in the Cartesian coordinate system. It is therefore proposed to move to a Cartesian coordinate system. H is coordinate similar φ, coordinate S - similar to ρ, and the coordinate V - is z. Translation HSV space coordinates to a Cartesian coordinate system can be configured according to the formulas (12).

$$\begin{cases} X_{hs} = \cos(H) \cdot S \\ Y_{hs} = -\sin(H) \cdot S, \\ Z_v = V \end{cases} \qquad (12)$$

where: X_{hs}, Y_{hs}, Z_v - the new values of the feature vector,

H, S, V – components of vector characteristics in HSV color space.

Methods for obtaining initial values of the clusters' centroids.

Algorithm for obtaining the initial values of cluster consists of the following stages:

Step 1. Arrange color space P_{HSV} on one-dimensional vectors P_H, P_S, P_V;

Step 2. Implement clustering in the resulting vectors. Vector is divided into intervals. For the initial value of the centroids of clusters are taken middle of intervals.

Step 3. Obtained cluster centroids are the coordinates of the centroids of the clusters in three-dimensional space of attributes HSV.

3 RESULTS AND DISCUSSION

3.1 An Example of a Cluster Analysis Algorithm with Self- Study

It was selected cluster analysis with self-study for digital image segmentation algorithm. Problem of cluster analysis is ensuring the reduction of a set of data in a more compact object classification (Baklanova and Uzdenbaev, 2013).

It is proposed method preliminary analysis brightness image zones in order to identify the initial value centroid of each cluster to ensure the quality of clustering and avoid possible location pseudo center.

It is used standard error deviation of the initial set of values from the cluster centers and rating (expressed as a percentage reflecting the relative quality of detail) to assess the quality of segmentation.

As a quantitative metric accessories cluster was chosen Euclidean distance:

$$D_{ik} = \left(\sum_{j=1}^{N}(x_{ij} - x_{jk})^2\right)^{\frac{1}{2}} \qquad (13)$$

where: i – index of the observation,

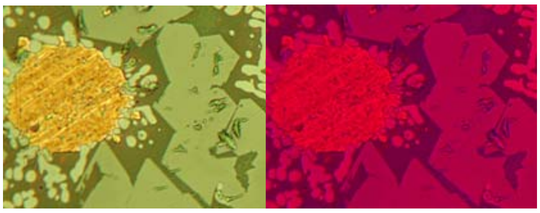
k – cluster index,

N – number of color space characteristics, (N=3),

x={x1,x2,x3} – vector in chosen color space.

Better results have been obtained after translation metrics color space HSV, to a Cartesian coordinate system XhsYhsZv (12).

Examples of clustering results are presented on Figures 4, 5, 6.



a) b)

Figure 3: Example of translation HSV-space algorithm: a) RGB-image, b) HSV-image.

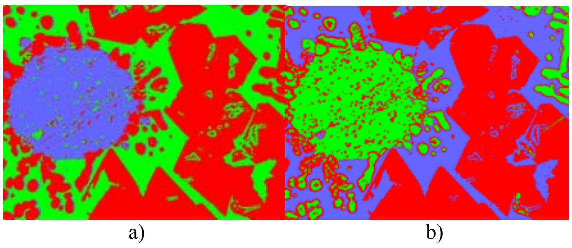


Figure 4: Example of clustering analysis for 3 clusters: a) RGB-image, b) HSV-image.

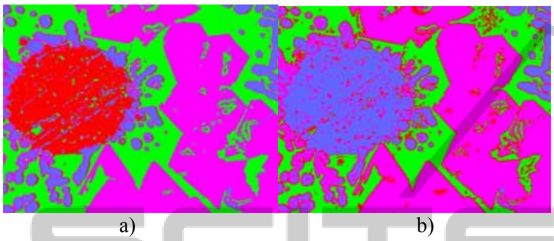


Figure 5: Example of clustering analysis for 4 clusters: a) RGB-image, b) HSV-image

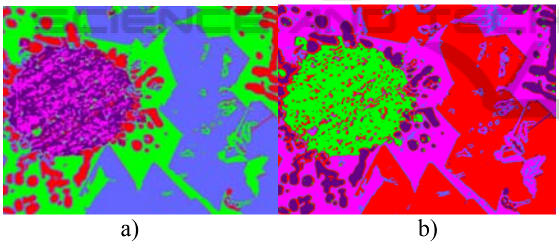


Figure 6: Example of clustering analysis for 5 clusters: a) RGB-image, b) HSV-image

3.2 Implementation of Cluster Analysis Algorithm for Computing Granulometries

Study of granulometric composition of rocks is produced by separating the constituent grain on size classes and to determine the weight of each class (Krasilnikov, 2011).

Weight of individual classes is expressed in percent. Size analysis is the most important type of research clastic rocks as their particle size distribution is the most important signs of defining all the other features: physical properties, geotechnical characteristics, mineral composition and other characteristics.

Tasks of granulometric analysis can be divided into 4 groups:

1) a precise definition of the structure and name of ore;

2) evaluation of ore as the mineral (soil, reservoirs of oil, gas, etc.);

3) reconstruction of the conditions for deposition (genesis) terrigenous sediment;

4) preparation for the study of other signs or other methods - chemical or mineralogical composition, grain shape and other features that are always different beans certain dimension.

Methods for determining the size of scattered objects on the image are important part of grit. It is possible to use the methods of cluster analysis to find the size of the objects, for example, k-means, i.e., without measuring the size of each individual object.

4 CONCLUSIONS

As a result it was determined color space provided sufficient quality rocks segmentation by the method of cluster analysis.

It was supposed the technique of pre- computing the values of the centroids. There is formulas translation metrics color space HSV. The effectiveness of the proposed method lies in the automatic identification of objects of interest on the total image, tuning parameters of the algorithm is a number that indicates the amount allocated to the segments. It has been developed practice software to investigate the methods.

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