Multi-color Space Features Analysis from Rock Shin-section Image for Rock-type classification

Ye Liu¹,³, Chao Guo², Fan Li¹, Lintao Lv¹, Dongchen Gao²
¹School of Computer Science, Xi'an Shiyou University, Xi'an 710065, Shaanxi, China
²Research Institute of Yanchang Petroleum (Group) CO.LTD, Xi'an 710075, Shaanxi, China
³Northwestern Polytechnical University, Xi'an 710072, Shaanxi, China
4368552@qq.com, 232003659@qq.com, 1594672629@163.com, 13289378981@163.com, 15364542@qq.com

Abstract: To fully analyze the features extracting from multi-color space for rock classification, each feature will be evaluated in this paper. And, to enhance correlation between features and reduce dimensionality of feature space, a PCA approach will be used and the result of PCA will also be fully analyzed. A C-SVM model is chosen to test analysis result. Data set consist of 500 images from Ordos basin. The classification result between single color space and multi-color space will be compared, and the cooperation result shows that features from multi-color space can support classifier like C-SVM to take higher accuracy and higher reliability.

1. INTRODUCTION
The foundation of image classification is features extracting from image. Features from different color space contain information about the sedimentary and diagenesis environment about rock, which are also essential for its physical property. For this purpose, features from each four color spaces are chosen to be fully analyzed in this paper, and then 12 features extracting from feature space with PCA also be analyzed.

An image processing and neural network based method proposed by Marmo(2005)¹ has been used in carbonate rocks classification. Aprile(2014)² proposed a similar image analysis and artificial neural networks combined approach for automatic classification of mineral inclusions and pores with optical digital images, and obtained encouraging result. Młynarczuk (2013)³ compared four pattern recognition methods on their automatic classifying effect. Furthermore, the difference between feature spaces extracted from four different color spaces was also evaluated. Yesiloglu-Gultekin(2012)⁴ developed a program to determine percentage values of minerals contained, and tested the program with granitic rock specimens. Ghiasi-Freez(2012)⁵ constructed a semi-automatic classifier to identify different types of porosity within reservoir rock. Perez(2015)⁶ extract the Gabor features under multi-scale from rock image, and recognized the minerals in it with an SVM classifier. And Francisco(2017)⁷ also used Gabor feature and additional LBP feature combined to build a SVM classifier to achieve rock components recognition. Jouini(2017)⁸ extracted rock textural features under a relative large scale with X-ray chromatography image. Each class of textural was compared
and analyzed in his research, and an SOM model was chosen to automatically classify the given rock samples.

Among all these research mentioned above, features always be the key element. But, research about features from different color space are inadequate. To provide the solutions to the above problem, four color space including RGB, HSV, YIQ and YCbCr consist so called multi-color spaces and combined with PCA to build feature space for rock type classification. In this paper, features in these color space included expectation and standard deviation of grey values and morphology gradient in different component matrix from these four color spaces. C-SVM will be utilized to map the relationship between the feature parameters extracted above and rock types.

2. BACKGROUND

2.1 The Class of Rock

(1) Type-I: fig.1-a, rock shows the most tight attribute in four types, and the particles of Type I rock are mainly consist of limestone, mudstone and siltstone. The characteristics of Type-I rock are: tiny particles, good separation and rounded. Only a few pores with scattered distribution are found in the Type-I samples (fig. 1-A).

(2) Type-II: This tight rock mainly consists of quartz sandstone with fine grains and lithic quartz sandstone which shows small grain size, poor sorting. Inter-granular pores are not highly developed in Type-II samples (fig. 1-B) and are most filled with the argillaceous content.

(3) Type-III: Consists of quartz sandstone. The grain size is larger, and the grinding and sorting degree are better. Some residual inter-granular pores can be found in Type-III samples (fig. 1-C).

(4) Type-IV: The composition of this relatively loose rock is mainly of quartz sandstone and a little rock debris and feldspar with coarse grains. The grain size is bigger, sorting degree is better. The quartz particles are generally overgrown and with brittle fractures. A lot of residual inter-granular pores, feldspar dissolved pores and micro fractures are developed in Type-IV samples (fig. 1-D).

As fig.1 shows, four representative types of rock are chosen to compare with each other. Type I represents deep water, weak hydrodynamic effect for its sedimental environment as fluvial, flood plain and bog. Type II is the delta front deposition and the transportation distance was short, the water power was strong. The sedimentary environments of Type III and Type IV, which is the fluvial of river delta sedimentary system, have similar sedimentary environment. And their main differences are from their diagenesis experiences. Type III represents rock under strong compaction effect. Type IV shows relatively strong effect by dissolution.

2.2 Color Space

In casting thin section, the color of casting determines the color of pore in image, and that is why color features show more significance for this classification. In addition, the samples used in this paper all come with red casting and from Odors Basin in China. Color models decompose each color into different components from different aspects that can extract more useful information by isolating themselves from interference from each other in chromatics, which define the concept of color space. Each of these four color spaces is chosen for its own specialty.

In next section, the correlation of each color space will be evaluated, which is a tough mission for the large number of features. To avoid this situation, 100 samples are randomly selected from total data set. And for each color space, only one intersection figure of two features will be chosen elaborately from total 66 figures for each space to express the correlation condition.
3. FEATURES ANALYSIS

3.1 RGB
RGB is one of the most widely used color space methods which separate a color into three components as Red, Green and Blue. Each of these components is assigned with a value between 0 - 255. That means with these components of RGB space, one can describe 256*256*256 colors which include all the color perceived by human vision.

Though casting injecting in sections is red in our samples, red component cannot properly describe chromatics properties of mineral, most of which show white, and pores, most of which shows red, for they settled in similar value range. As shown in fig.3, compared to R, G and B expose to be the two most concerned components, especially for G, which can produce more details about pores and minerals.

In fig.2, is the intersection figure of green component std and green component mean. From this figure type-I can be recognized simply, but the other types are still in a certain extent of mixture condition. Though RGB is the most common color space, it cannot fully evaluate the pore features in section image, given its limitations for limited numbers of color definitely limit the information detail expression and ignore the effect on brightness and saturation caused by image acquisition conditions difference.

3.2 HSV
HSV(Hue, Saturation and Value) is a color perceptual intuition feature based color space, also called Hexcone Model proposed by A. R. Smith(1978). HSV is a user-oriented color model that is different from RGB which is hardware-oriented with three components of hue(H), saturation(S), and value(V). Compared to RGB, HSV brings more information about saturation and brightness which are more proper for segmentation of threshold as pore recognition in classification usage. Though HSV shows many advantages, still has some disadvantages for its incapability in some image processing arithmetic of illumination model as light intensity and light mixture.

As in fig.4, in the intersection figure of S component mean value and S component morphological gradient, four types of sand rocks have better segmentation result with only Type-II and Type-III having some overlap. From fig.5, in each component of HSV, pore space and mineral can be identified clearly, especially in S component. In H component, hue value provides more details of mineral texture, matrix filled into pore and the edge between pore and minerals. HSV shows best classification effect in four color spaces.

3.3 YIQ
YIQ is similar with HSV, which also brings brightness as a component of color model, but instead of saturation with two components of hue. YIQ is relatively simple color space for the linear transformation relation between RGB and itself. The advantages YIQ is based on its ability of separating brightness and hue totally with less computed quantity and better cluster effect.

Features from YIQ show less correlation with rock types than HSV’s. Intersection figure of Y component means value and I component morphological gradient is showed in fig.6. From fig.6, one
can infer that morphological gradient can help to identify Type-IV from other types, and recognition of Type-I–III mainly relies on Y component. In fig.7, similar with HSV, hue value presents a little contribution to classification especially in Q component, and Y component, representing brightness of image, contains more information than hue components. I (C) and Q (D) components both representing chrominance information shows obvious difference. Compared with (C), Q component (D) can hardly extract any available information, as I component represents red to blue color, which represents casting color in thin section, and Q component represents purple to green.

Fig. 2. Intersection figure, vertical and horizontal axis represent std value and mean value of G component in RGB, colors of point represents types of rock as blue: Type-I, yellow: Type-II: green: Type-III, red: Type-IV.

Fig. 3. Orginal casting thin section image(A) and three grey value images corresponding three components of Red(B) Green(C) and Blue(D).

3.4 YCbCr
YCbCr derives from YUV model is a common color space used in video processing and digital photography system. YCbCr is an essential space in this classification mission as the casting injected into pore space always takes red or blue color. And Cb and Cr components represent blue and red color respectively corresponding casting color directly. By wiping off the brightness effect from Y component, Cb and Cr can express a pure color factor matrix which ignores the influence from light change under different acquisition conditions.
Fig. 4. Intersection figure, vertical axis represents mean value of morphological gradient in S component and horizontal axis represents mean value of S component in HSV, colors of point represents types of rock as blue: Type-I, yellow: Type-II, green: Type-III, red: Type-IV.

![Intersection figure](image)

Fig. 5. Original casting thin section image (A) and three grey value images corresponding three components of Hue (B) Saturation (C) and Value (D).

![Images](image)

Fig. 6. Intersection figure, vertical axis represents std value of morphological gradient in I component and horizontal axis represents mean value of Y component in YIQ, colors of point represents types of rock as blue: Type-I, yellow: Type-II, green: Type-III, red: Type-IV.

![Intersection figure](image)
Fig. 7. Original casting thin section image (A) and three grey value images corresponding three components of Luma (B) In-phase (C) and Quadrature (D).

Fig. 8. Intersection figure, vertical axis represents std value of Cr component and horizontal axis represents mean value of Y component in YCbCr, colors of point represents types of rock as blue: Type-I, yellow: Type-II: green: Type-III, red: Type-IV.

Fig. 9. Original casting thin section image (A) and three grey value images corresponding three components of Y (B) Cb (C) and Cr (D).

As in fig.8, std value of Cr component as the other red hue component prominent Type-IV samples from others. And the brightness of component Y shows good segmentation result for Type-I–III similar to Y component in YIQ. In YCbCr, Cr representing red color is totally different from R in RGB, as in fig.9(B) and fig.3(B). The main difference between YCbCr and RGB is in the mineral part,
where the white color of mineral is separated into Y component of YCbCr without any residual value Cr component, different from R component in RGB.

4. EXPERIMENTAL RESULTS

From the cross-plot mentioned above, features extracted from each single color space present its specific advantage and shortage in classification. An example of classification test of single RGB color space with three times random sampling from sample set shows in Table I. As in Table I, Class IV shows lowest classification accuracy, and the total accuracy only up to 79% which can’t fulfill the demands of classification accuracy.

| Experimental No. | Color Space | Class I | Class II | Class III | Class IV | Total accuracy |
|------------------|-------------|---------|----------|-----------|-----------|---------------|
| 1                | YIQ         | 88      | 80       | 84        | 32        | 70            |
| 2                | HSV         | 84      | 76       | 84        | 56        | 75            |
| 3                | YCbCr       | 84      | 76       | 84        | 72        | 79            |
| Average accuracy |             | 85.3    | 77.3     | 84        | 53.3      | 74.7          |

Same test has been provided to each single color space of YIQ, HSV and YCbCr with similar problems. Single color space based classification method shows great inaccuracy and unstable of classification. That’s the reason for the multi-color space classification method proposed here trying to improve the accuracy and stability of classifier.

![Classification results under different color spaces](image)

Fig. 10. Classification results under different color spaces (1.YIQ; 2.HSV; 3.YCbCr)

For the disadvantages as low accuracy etc. showing in Tab.1 and Fig.10, features from single color space will be instead of multi-color space with same classifier to test the classification improvement. With the same train dataset as single color space in Tab.1, the trained C-SVM classifier get over 96% accuracy in 20 times test.

5. CONCLUSIONS

In this paper, features from multi-color space of rock thin section images are extracted. Then the correlation between different features and rock types are analyzed, which reveal the reason of single color space deficiency. In experimental test, a C-SVM model is chosen to compare the performance of multi-color space and single color space in rock classification problem, demonstrating features from multi-color space could bring more valuable information to improve the classification accuracy and reliability.

Acknowledgment

This work was supported by Shaanxi Provincial Natural Science Basis Research 2018 with the Project No.2018JM4004 and 2018JM4005, Special scientific research project of Education Department of Shaanxi Province of China undergrant 17JK0603.
References

[1] Marmo R, Amodio S, Tagliaferri R, et al. Textural identification of carbonate rocks by image processing and neural network: Methodology proposal and examples[J]. Computers & geosciences, 2005, 31(5): 649-659.

[2] Aprile A, Castellano G, Eramo G. Combining image analysis and modular neural networks for classification of mineral inclusions and pores in archaeological potsherds[J]. Journal of Archaeological Science, 2014, 50: 262-272.

[3] Młynarczuk M, Górszczyk A, Ślipek B. The application of pattern recognition in the automatic classification of microscopic rock images[J]. Computers & Geosciences, 2013, 60: 126-133.

[4] Yesiloglu-Gultekin N, Keceli A S, Sezer E A, et al. A computer program (TSecSoft) to determine mineral percentages using photographs obtained from thin sections[J]. Computers & Geosciences, 2012, 46: 310-316.

[5] Ghiasi-Freez J, Soleimanpour I, Kadkhodaie-Ilkhchi A, et al. Semi-automated porosity identification from thin section images using image analysis and intelligent discriminant classifiers[J]. Computers and Geosciences, 2012, 45: 36-45.

[6] Perez C A,Saravia J A, Navarro C F, et al. Rock lithological classification using multi-scale Gabor features from Sub- images, and voting with rock contour information[J]. International Journal of Mineral Processing,2015,144:56–64.

[7] Francisco J. Galdames, Claudio A. Perez,Pablo A. Estévez,et al. Classification of rock lithology by laser range 3D and color images[J]. International Journal of Mineral Processing, 2017: 47–57.

[8] Jouini M S, Keskes N. Numerical estimation of rock properties and textural facies classification of core samples using X-Ray Computed Tomography images[J]. Applied Mathematical Modelling,2016.