Rock Image Classification Using Non-Homogenous Textures and Spectral Imaging

Leena Lepistö[1], Iivari Kunttu[1], Jorma Autio[2], and Ari Visa[1]

[1] Tampere University of Technology
Institute of Signal Processing
P.O. Box 553, FIN-33101 Tampere, Finland
Tel. +358 (0)3 31154964
E-mail: Leena.Lepisto@tut.fi

[2]Saanio & Riekkola Consulting Engineers
Laulukuja 4
FIN-00420 Helsinki, Finland
Tel. +358 (0)9 5666500
E-mail: Jorma.Autio@sroy.fi

ABSTRACT

Texture analysis and classification are usual tasks in pattern recognition. Rock texture is a demanding classification task, because the texture is often non-homogenous. In this paper, we introduce a rock texture classification method, which is based on textural and spectral features of the rock. The spectral features are considered as some color parameters whereas the textural features are calculated from the co-occurrence matrix. In this classification method, non-homogenous texture images are divided into blocks. The feature values are calculated for each block separately. In this way, the feature values of the texture image can be presented as a feature histogram. The classification method is tested using two types of rock textures. The experimental results show that the proposed features are able to distinguish rock textures quite well.

Keywords

Texture classification, Non-homogenous textures, Spectral Imaging, Rock Images

1. INTRODUCTION

In the field of pattern recognition, different texture types are commonly studied topics. Texture is an important characteristic of many image types, and it can be used for example in image segmentation. Textures can be divided into two categories: deterministic and stochastic textures [Iiv98]. The deterministic textures consist of repetitive similar patterns, whereas the stochastic ones obey only some statistical laws. Most of the real world textures, like grass or ice, are stochastic. A collection of different texture types is introduced by Brodatz [Bro68].

An example of natural textures is rock texture. Analysis of rock texture is quite demanding. Unlike most of the Brodatz textures, rock texture is in many cases non-homogenous and strongly directional. Also granular size and color of the texture may vary significantly in some rock texture types. Due to these properties, analysis and classification of rock textures is a difficult task.

The motivation of the work presented in this paper is related to control of quality and production of rock samples. In the field of rock research, the development of digital imaging has made possible to analyze and classify the rock samples in digital form. In rock and stone industry one basic problem is classification of the rock samples. It is essential for the manufacturer to be able to classify the rock samples in visually similar classes. For example, stone plates in walls of buildings are often required to appear visually similar. This classification conventionally carried out manually based on experience. However, in digital form, the rock samples can be analyzed and classified in automatic way. Some research works on this topic have been published. In our previous work [Lep02], we developed the feature extraction of rock texture images. Autio et al [Aut99] present classification procedure of the rock textures. The classifying features were based on the co-occurrence matrix and Hough transform. Lebrun et al have published several studies on rock imaging and analysis. In [Leb00] they present a rock sample imaging system and color analysis in L*a*b* color space. Color image analysis is applied to the inspection of marble tiles in [Leb01]. Bruno et al used different statistical and spectral methods to characterize and classify ornamental stone samples [Bru99]. The methods in

WSCG SHORT PAPERS proceedings
WSCG'2003, February 3-7, 2003, Plzen, Czech Republic.

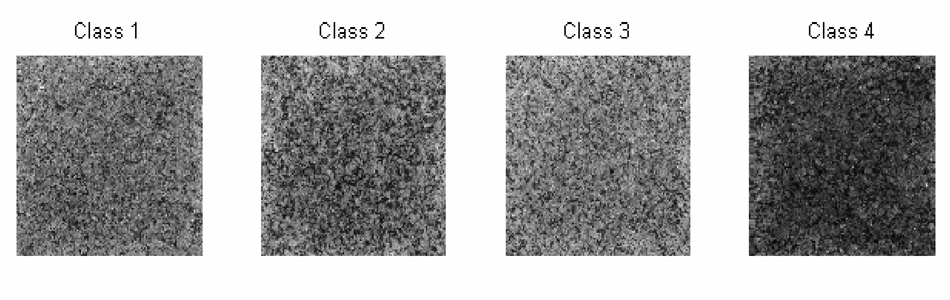

Figure 1. Example samples of texture classes of type I.

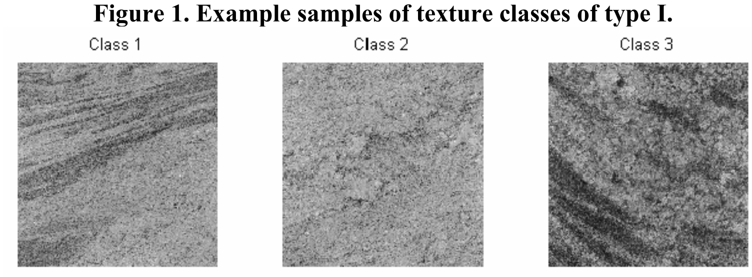

Figure 2. Example samples of texture classes of type II.

their research were RGB color histograms, variograms, and size-intensity diagrams.

One point of view to rock texture analysis is the spectrum of the texture image. The spectrum of light reflecting from the rock carries significant amount of the information about the texture. One of the main topics of this paper is to concentrate on the extraction of the spectrum information from the rock texture. We describe this in more detail in the section 2. In addition to the spectrum, we consider also textural properties of the rock. Commonly used classifying features of texture are measures calculated from the gray level co-occurrence matrix. We use some of these measures to distinguish between the rock textures. Experiments based on the texture properties and the spectrum of some rock images are presented in the section three. Finally, the results of this work are discussed in section four.

2. FEATURE ANALYSIS

In order to make an automated classification between different rock textures, some classifying features have to be extracted from the texture. In this part of this work we introduce two feature types, spectrum-based features and statistical measures calculated from the co-occurrence matrix.

Features based on the spectrum

The light, which reflects from the rock, forms a spectrum. The visible part of the spectrum of light is located between 400 and 700 nm. Characterization of the light is related to science of color. If the light is achromatic, its only attribute is intensity. The scalar measure of reflectance is gray level [Gon93]. All colors are seen as variable combinations of the three primary colors, red (R), green (G) and blue (B). The specific wavelength values for these colors have been designated by CIE in 1931 [Gon93],[Wys82], and they are 435.8 nm, 546.1 nm and 700 nm for blue, green and red, respectively.

Combination of three primary colors is useful in spectrum measurement, when the visible part of the spectrum is considered. However, to extract the spectrum information from the texture image, the consideration should be done in HSI-model. In the HSI-model hue (H) describes a pure color, whereas the saturation (S) gives the measure of degree to which a pure color is diluted by white light. Intensity (I) is decoupled from the color information of the image [Gon93]. In this work, we use hue and intensity information:

$$H = \cos^{-1}\left\{ \frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}} \right\} \tag{1}$$

$$I = \frac{1}{3}(R+G+B) \tag{2}$$

Textural features

Grey-level co-occurrence matrix [Har73],[Vis90] is a second order statistical measure, which is based on the spatial gray level dependence. It is widely applied in the texture analysis, and also in classification of the rock textures [Aut99]. The co-occurrence matrix is based the estimation of the second order joint probability density functions $g(i,j \mid d,\Theta)$. Each of them is the probability of going from gray level i to gray level j, when the intersample spacing is d and the direction is Θ. The probabilities create a co-occurrence matrix $M(i,j \mid d,\Theta)$. Several texture features can be calculated from the matrix. Most useful of them for rock texture analysis [Aut99], [Lep02] have proved to be contrast and entropy:

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 M(i,j \mid d,\Theta) \tag{3}$$

$$\text{Entropy} = -\sum_i \sum_j M(i,j \mid d,\Theta) \log M(i,j \mid d,\Theta) \tag{4}$$

Properties related to texture are usually defined from gray level images. In case of the rock textures we can simply use texture intensity calculated by the HSI-transform.

3. EXPERIMENTS

A set of industrial rock images was acquired in controlled conditions for testing purposes. The test set contained 118 images, which represented two typical rock texture types found in Finland. Size of the rock sample was 300x300 mm (image size 1430x1430 pixels).

In the first texture set of type I, there were 54 samples of relatively homogenous rock texture with small variations in color. The rock manufacturer had divided the samples into four classes, which had similar texture but different color. An example of each class is presented in figure 1. The second texture set of type II consisted of 64 non-homogenous anisotropic gneissic rock texture samples. In these samples there were strong differences in texture and color. These features varied significantly also within the same samples of this type. By means of these features, the samples of this type were divided subjectively into three classes by an expert. An example of each class is presented in figure 2.

Classification of the texture samples was based on the k-nearest neighbor method [Dud01]. This method is valid because of non-symmetric feature distributions. In this method the class of each sample is defined by means of k samples, which are nearest to the unknown sample. The class of the unknown sample is decided to be the same as the classes of its nearest neighbors. In all the classification experiments, leave one out validation method [Dud01] was used.

Classification of homogenous textures

Texture classification of sample set of type I was based on the features introduced in section 2. The texture features were calculated for each sample and the spectral features were defined as a mean value of each sample. The classification was made for each of four features individually, using the k-nearest neighbor classifier. In the classification, the value of k was experimentally selected to be 3. Table 1 presents the result of the classification. The table gives the number of samples assigned to each of the four classes. In this case, spectral features mean hue and mean intensity, gave clearly the best results. The differences between the classes can be seen in figure 3, which presents the plot of these features for type I texture samples.

Classification of non-homogenous textures

Red rock samples in type II represented non-homogenous textures. In case of these textures, the texture and color parameters have significant differences within the same samples. Therefore an approach was taken based on the division of rock images into smaller blocks and analysis of these blocks. The distribution of the block feature values of each sample can be regarded as a feature histogram. Similar rock texture samples can be found by matching these feature histograms of the samples. The distance measure D for this purpose is L_1-norm [Dud01]:

$$D = \sum_{i=1}^{n} \left| h_1(i) - h_2(i) \right| \tag{5}$$

in which h_1 and h_2 are histograms and n is the number of bins of them. Using this principle the classification of strongly non-homogenous rock texture samples is possible.

Contrast	Assigned class:			
True class:	**1**	**2**	**3**	**4**
1	15	0	1	0
2	1	3	9	0
3	1	12	0	0
4	0	0	0	12

Entropy	Assigned class:			
True class:	**1**	**2**	**3**	**4**
1	15	1	0	0
2	3	7	3	0
3	0	1	12	0
4	0	0	0	12

Mean hue	Assigned class:			
True class:	**1**	**2**	**3**	**4**
1	16	0	0	0
2	0	13	0	0
3	0	0	13	0
4	0	0	0	12

Mean Int.	Assigned class:			
True class:	**1**	**2**	**3**	**4**
1	13	2	1	0
2	3	10	0	0
3	1	0	12	0
4	0	0	0	12

Table 1. Classification results of type I textures using 3-nearest neighbor classifier.

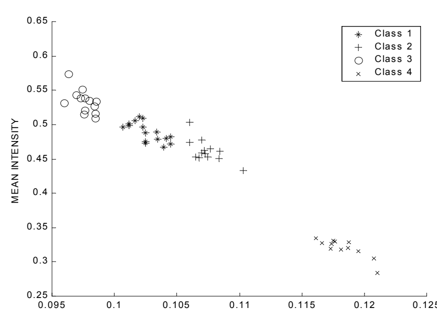

Figure 3. Mean hue-mean intensity plot of type I textures.

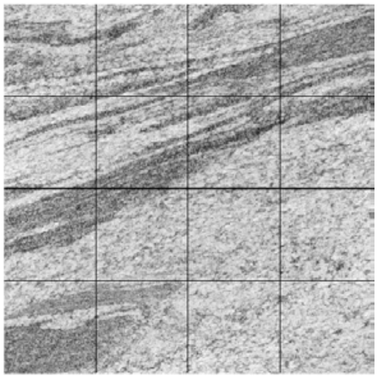

Figure 4. Division of a non-homogenous rock sample into 16 blocks.

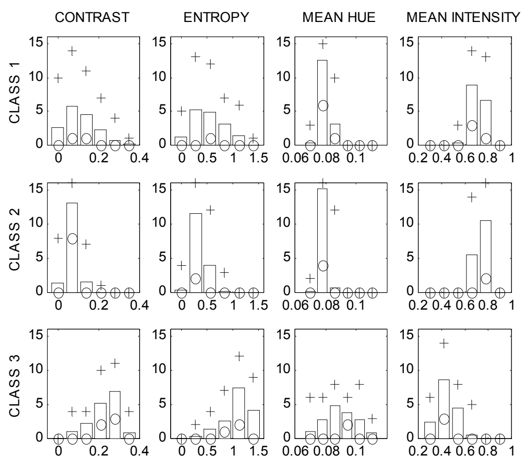

Figure 5. Mean feature histograms of type II rock texture samples in three classes. Maximum is marked with + and minimum with o.

We divided type II texture samples into 16 blocks (figure 4). The number of the blocks was selected by means of earlier research. The spectral features, mean hue and mean intensity, as well as texture features contrast and entropy were calculated for each block. Based on these values feature histograms were formed for each sample. The mean of the histogram of each sample class is presented in figure 5.

For each 64 samples of type II textures, we defined the distance *D* between the sample and the other samples. The classification was made using the 3-nearest neighbor classifier. The results of the classification in each class are presented in table 2. The results show that in case of the non-homogenous textures, the best results can be obtained using the textural features contrast and entropy. The computing time for feature calculation was 38 sec for each sample using Matlab on a PC with 804 MHz Pentium III CPU and 256 MB primary memory.

Contrast	Assigned class:		
True class:	1	2	3
1	9	4	1
2	0	40	0
3	2	0	8

Entropy	Assigned class:		
True class:	1	2	3
1	10	4	0
2	1	39	1
3	1	0	9

Mean hue	Assigned class:		
True class:	1	2	3
1	7	7	0
2	1	38	1
3	1	0	9

Mean Int.	Assigned class:		
True class:	1	2	3
1	7	7	0
2	2	38	0
3	0	0	10

Table 2. Classification results of type II textures using 3-nearest neighbor classifier.

4. DISCUSSION

In this paper we considered the classification problem of the rock textures. In the texture classification we used two types of features, textural and spectral features. The textural features are based on the gray level co-occurrence matrix, which is commonly used tool in the texture classification. On the other hand, the spectrum of the texture is a new approach to rock image classification. In this research we considered the spectrum as color channels, and therefore we were able to use the well-known color transforms in the feature extraction.

We had two types of rock texture samples for testing purposes. Using these samples we were able to test the classification both homogenous and non-homogenous rock textures. In case of homogenous texture samples the spectral features were clearly better, whereas the textural features were better in the classification of the non-homogenous textures. This result shows that each feature introduced in this paper is significant for certain rock texture type. Despite the fact that classification of the rock samples is difficult task even for an expert, the proposed features gave good results. In conclusion, the classification results can be improved by combining these features.

This paper presents a new approach to classification and analysis of non-homogenous rock textures. In general, this is a difficult classification task due to strong differences within the samples. The new solution for this problem is to divide the non-homogenous samples into the blocks. In this way, different areas of the non-homogenous texture sample can be considered separately. Therefore, well-known texture analysis methods, like co-occurrence matrix, give significantly better classification results. In the experiments presented in this paper, classification based on the distributions of the block features gave relatively good results. Therefore our approach proved to be useful in classification of non-homogenous rock textures. These results have practical significance in rock and stone industry. In that application area the classification methods presented in this paper can be used to classify rock samples into visually similar classes.

Because of encouraging results presented in this paper, the idea of block division of the texture can be also a subject for further studies. One approach would be to alter the size and shape of the blocks in classification. This could yield to more accurate classification. The non-homogenous rock textures are also often strongly directional. This fact could be used as a subject of future research in this field. Also different color spaces can be tested in color-based classification of the rock texture samples.

5. ACKNOWLEDGMENT

We would like to thank Consulting Engineers Saanio & Riekkola Oy and the Technology Development Centre of Finland (TEKES's grant 40397/01) for financial support.

6. REFERENCES

[Aut99] Autio, J., Luukkanen, S., Rantanen, L., and Visa, A. The Classification and Characterisation of Rock Using Texture Analysis by Co-occurrence Matrices and the Hough Transform, International Symposium on Imaging Applications in Geology, pp. 5-8, Belgium, May 6-7 1999.

[Bro68] Brodatz, P. Texture: A photographic Album for Artists and Designers, Reinhold, New York, 1968.

[Bru99] Bruno, R., Persi paoli, S., Laurenge, P., Coluccino, M., Muge, F., Ramos, V., Pina, P., Mengucci, M., Cica Olmo, M., Serrano Olmedo, E. Image Analysis for Ornamental Stone Standard's Characterisation, International Symposium on Imaging Applications in Geology, pp.29-32, May 6-7, 1999

[Dud01] Duda, R. O., Hart, P. E. and Stork, D. G. Pattern Classification, 2nd edition, John Wiley & Sons, New York, 2001.

[Har73] Haralick, R. M., Shanmugam, K., Dinstein, I. Textural Features for Image Classification. IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC 3, No. 6, Nov 1973.

[Gon93] Gonzalez, R. C., and Woods, R. E. Digital Image Processing, Addison Wesley, United States of America, 1993.

[Iiv98] Iivarinen, J. Texture Segmentation and Shape Classification with Histogram Techniques and Self-Organizing Maps, Acta Polytechnica Scandinavica, Mathematics, Computing and Management in engineering series No 95, Doctor of Science Thesis, Espoo 1998.

[Leb00] Lebrun, V. Toussaint, C., Pirard, E. On the use of image analysis for the quantitative monitoring of stone alteration. Weathering 2000 International Conference, Belfast, 2000

[Leb01] Lebrun, V. and Macaire, L Aspect inspection of marble tiles by colour line-scan camera, QCAV'2001, Le Creusot, 2001.

[Lep02] Lepistö, L., Kunttu, I., Autio, J., and Visa, A. Comparison of Some Content.Based Image Retrieval Systems with Rock Texture Images, Proceedings of 10th Finnish Artificial Intelligence Conference, Oulu, Finland, pp. 156-163, Dec. 16-17, 2002.

[Vis90] Visa, A. Texture Classification and Segmentation Based on Neutral Network Methods, Doctor of Science Thesis, Espoo, 1990.

[Wys82] Wyszecki, G. and Stiles, W. S. Color Science, Concepts and Methods, Quantitative Data and Formulae, 2nd Edition, John Wiley & Sons, Canada, 1982.