*Impact Factor (SJIF): 4.542*

**International Journal of Advance Research in Engineering, Science & Technology**

*e-ISSN: 2393-9877, p-ISSN: 2394-2444*

***Volume 4, Issue 3, March-2017***

# Image Classification Using Non-Homogenous Textures Analysis

Amit Pathare[1], Sanket Nirmal[2]

*Department of Electronics & Telecommunication Engg. PRMITR, Badnera*

*Department of Electronics & Telecommunication Engg. PRMITR, Badnera*

**Abstract—Texture analysis and classification are usual tasks in pattern recognition. In this paper, a texture classification method is used, which is based on textural features of the object. The textural features are calculated from the co-occurrence matrix. In the case of natural images, the feature distributions are often non-homogenous and the image classes are also overlapping in the feature space. This can be problematic, if all the descriptors are combined into a single feature vector in the classification. A method is presented for combining different visual descriptors in image classification. In this approach, k-nearest neighbour classification is first carried out for each descriptor separately. After that, the final decision is made by combining the nearest neighbours in each base classification. The total numbers of the neighbours representing each class are used as votes in the final classification.**

**Keywords—Texture classification, Non-homogenous textures, Spectral Imaging, k-nearest neighbour voting**

## I. 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 [9]. 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 [4]. An example of natural textures is rock texture. Analysis of rock texture is quite demanding. Unlike most of the Brodatz textures, rock texture in many cases is 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 [1].

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. Autio et al [3] present classification procedure of the rock textures. The classifying features were based on the co-occurrence matrix and Laws Mask method (Hough transform). Bruno et al used different statistical and spectral methods to characterize and classify ornamental stone samples [5]. The methods in their research were RGB color histograms, variograms and size-intensity diagrams.

Commonly used classifying features of texture are measures calculated from the gray level co-occurrence matrix. Some of these measures are used to distinguish between the rock textures. The division of natural images such as rock, stone, clouds, ice or vegetation into classes based on their visual similarity is a common task in many machine vision and image analysis solutions.

Classification of natural images is demanding, because in the nature the objects are seldom homogenous. For example, when the images of rock surface are inspected, there are often strong differences in directionality, granularity or color of the rock, even if the images represented the same rock type. In addition to non-homogeneities, the feature patterns can also be noisy and overlapping, which may cause variations in the decision surfaces of different classifiers. Owing to these reasons, different classifiers may classify the same image in different ways. These kinds of variations and non-homogeneities make it difficult to classify these images accurately, using a single classifier. On the other hand, non-homogenous feature distributions of certain image types may also improve classification of these images in certain classifiers. Thus the fact that different

All Rights Reserved, @IJAREST-2017

classifiers often give varying decisions can be utilized in the classification. It has been found that a consensus decision of several classifiers can often give better accuracy than any single classifier. This fact can be easily utilized in the classification of real world images. [2]

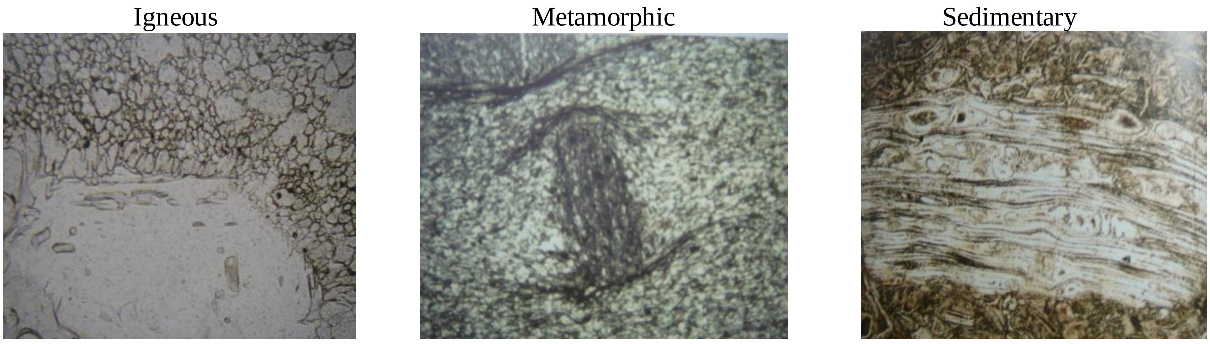



Figure 1. Example Samples of Texture classes

## II. FEATURE ANALYSIS

In order to make an automated classification between different rock textures, some classifying features have to be extracted from the texture.

Generally there are two feature types, spectrum based features and statistical measures calculated from the co-occurrence matrix.

***A. Textural features***

Grey-level co-occurrence matrix [7], [13] 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 [3]. 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 $\Theta$. The probabilities create a co-occurrence matrix $M(i,j|d,\Theta)$. Several texture features can be calculated from the matrix. There can be 28 textural features can be extracted from each co-occurrence matrix [7]. Most useful of them for rock texture analysis [3], [12] have proved to be contrast and entropy:

$$contrast = \sum_i \sum_j (i-j)^2 M(i,j \mid d,\Theta) \qquad (1)$$

$$Entropy = \sum_i \sum_i M(i,j \mid d,\Theta) \log \frac{1}{M(i,j \mid d,\Theta)} \qquad (2)$$

Properties related to texture are usually defined from gray level images.

## III. EXPERIMENTS

A set of rock images was acquired in controlled conditions for testing purposes (Vernom images), some of which as shown in figure 1. The test set contained 73 Igneous images, 113 Metamorphic images and 23 sedimentary images. Size of the rock sample was of image size 1280x960 pixels.

Rock images are divided into three classes, each with different texture feature, namely igneous, metamorphic and sedimentary. An example of each class is presented in figure 1. In these samples there were strong differences in texture and colour. The texture features varied significantly also within the same samples of this type.

Classification of the texture samples was based on the $k$-nearest neighbour method [6]. 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 neighbours. In all the classification experiments, leave one out validation method [6] was used.

Some of the results obtained using co-occurrence method is shown in figure 2 and figure 3. The results are obtained by changing the direction $\Theta$ so as to achieve the rotation invariant. By changing the intersample distance $d$, scaling invariant can be achieved [1].

All Rights Reserved, @IJAREST-2017

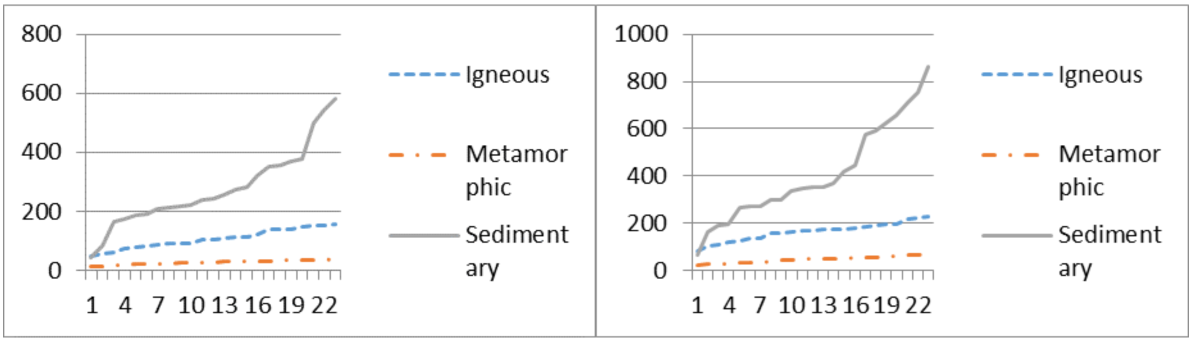



Figure 2. a) Contrast $d=1$, $\Theta=0^0$ b) Contrast $d=1$, $\Theta=45^0$

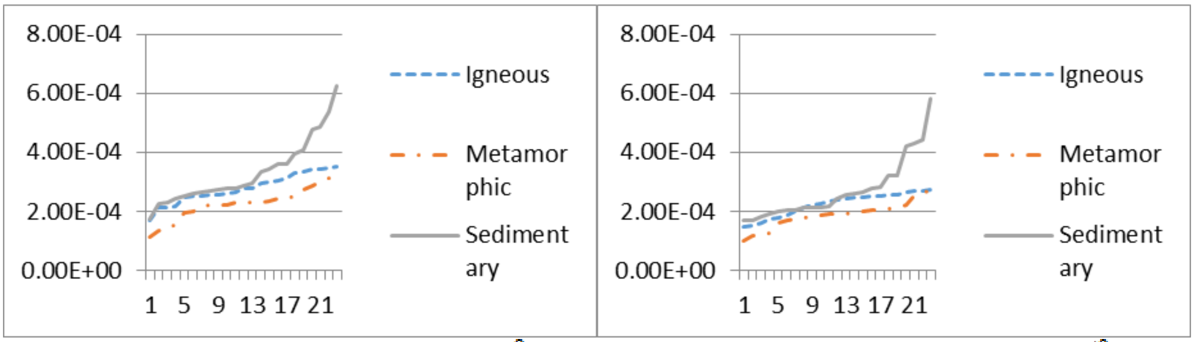


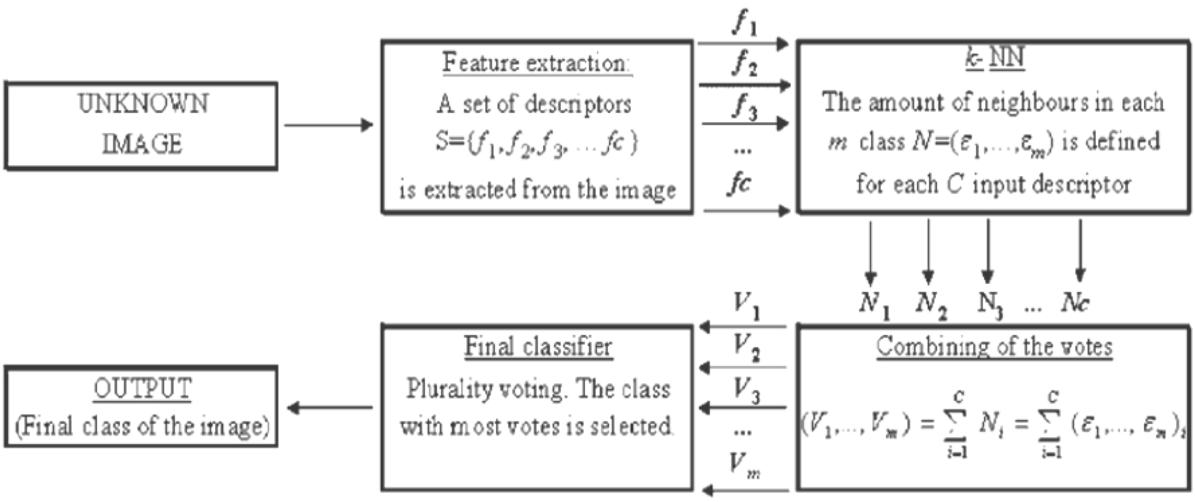

Figure 3. a) Energy $d=1$, $\Theta=0^0$ b) Energy $d=1$, $\Theta=45^0$

### *A. Classification of non-homogenous textures*

Red rock samples e.g. sedimentary rock represented non homogenous textures. In case of these textures, the texture and colour parameters have significant differences within the same sample. 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 [6]:

$$D = \sum_{i=1}^{n} |h_1(i) - h_2(i)| \tag{3}$$

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 sample is possible. The outline of classifier shown is figure 4.




All Rights Reserved, @IJAREST-2017

## IV. CONCLUSION

In this paper, the problem of feature extraction and classification of the rock textures is considered. In the texture classification, textural type of features were used. The textural features are based on the gray level co-occurrence matrix, which is commonly used tool in the texture classification.

There are three types of rock texture samples for testing purposes. Using these samples it is possible to test the classification of non-homogenous rock textures. The textural features were better in the classification of the non-homogenous textures. The 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 will give good results. In conclusion, the classification results can be improved by combining multiple 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 the 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.

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.

## REFERENCES

[1] Leena Lepisto, Iivari Kunttu, Jorma Autio, and Ari Visa. Rock Image Classification Using Non-Homogenous Textures and Spectral Imaging. Spectral, WSCG SHORT PAPERS proceedings, Plzen, Czech Republic, WSCG'2003.
[2] L. Lepisto, I. Kunttu and A. Visa. Rock image classification based on k-nearest neighbour voting. IEEE Trans. vol:153, pp:475-482,2006
[3] 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.
[4] Brodatz, P. Texture: A photographic Album for Artists and Designers, Reinhold, New York, 1968.
[5] 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
[6] Duda, R. O., Hart, P. E. and Stork, D. G. Pattern Classification, 2nd edition, John Wiley & Sons, New York, 2001.
[7] 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.
[8] Gonzalez, R. C., and Woods, R. E. Digital Image Processing, Addison Wesley, United States of America, 1993.
[9] 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.
[10] 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
[11] Lebrun, V. and Macaire, L Aspect inspection of marble tiles by colour line-scan camera, QCAV'2001, Le Creusot, 2001.
[12] Lepisto, 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.
[13] Visa, A. Texture Classification and Segmentation Based on Neutral Network Methods, Doctor of Science Thesis, Espoo, 1990.
[14] Wyszecki, G. and Stiles, W. S. Color Science, Concepts and Methods, Quantitative Data and Formulae, 2nd Edition, John Wiley & Sons, Canada, 1982.

All Rights Reserved, @IJAREST-2017