ROCK TEXTURE RETRIEVAL USING GRAY LEVEL CO-OCCURRENCE MATRIX

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ABSTRACT

Nowadays, as the computational power increases, the role of automatic visual inspection becomes more important. Therefore, also visual quality control has gained in popularity. This paper presents an application of gray level co-occurrence matrix (GLCM) to texture-based similarity evaluation of rock images. Retrieval results were evaluated for two databases, one consisting of the whole images and the other with blocks obtained by splitting the original images. Retrieval results for both databases were obtained by calculating distance between the feature vector of the query image and other feature vectors in the database. Performance of the co-occurrence matrices was also compared to that of Gabor wavelet features. Co-occurrence matrices performed better for the given rock image dataset. This similarity evaluation application could reduce the cost of geological investigations by allowing improved accuracy in automatic rock sample selection.

1 INTRODUCTION

The role of automatic visual inspection has grown up during the last decade in the same way as the computational power has increased and the prize of computation has decayed. Visual inspection, especially, in the sense of visual quality control has gained in popularity. Nowadays, several commercial applications are available e.g. in paper mills [7-8], in saw mills [9], and in rock industry [10]. Most of these applications are based on texture classification. However, we are now concerned with the problem of how to guarantee even quality within a set of rock plates. When raw stone is broken into plates it is essential that all the plates within a category are of even quality. The color and the texture of rock plates play a significant role. In this paper we will consider only the texture.

Visual texture contains variations of intensities, which form certain repeated patterns. Those patterns can be caused by physical surface properties, such as roughness, or they could result from reflectance differences, such as the color on a surface. Differences observed by visual inspection are difficult to define in quantitative manner, which leads to demand of defining texture using some features. Because of their stochastic nature rock textures can be characterized by statistical means into first-, second- and higher order statistics. Since human perception has been found to be sensitive to second order statistics, this paper concerns texture similarity estimation based on them. The goal of this study is to examine how the most similar texture images can be retrieved automatically for the given query image. The retrieval is based on the features extracted from the gray level co-occurrence matrix (GLCM)[1], which is a well known method for analyzing texture images.

2 USED METHOD

Gray level co-occurrence matrix (GLCM)[1], one of the most known texture analysis methods, estimates image properties related to second-order statistics. Each entry (i,j) in GLCM corresponds to the number of occurrences of the pair of gray levels i and j which are a distance **d** apart in original image.

In order to estimate the similarity between different gray level co-occurrence matrices, Haralick [1] proposed 14 statistical features extracted from them. To reduce the computational complexity, only some of these features were selected. The description of 4 most relevant features that are widely used in literature [3-5] is given in Table1.

Energy, also called Angular Second Moment [1] and Uniformity in [3], is a measure of textural uniformity of an image. Energy reaches its highest value when gray level distribution has either a constant or a periodic form. A homogenous image contains very few dominant gray tone transitions, and therefore the P matrix for this image will have fewer entries of larger magnitude resulting in large value for energy feature. In contrast, if the P matrix contains a large number of small entries, the energy feature will have smaller value.

Entropy measures the disorder of an image and it achieves its largest value when all elements in P matrix are equal [3]. When the image is not texturally uniform many GLCM elements have very small values, which implies that entropy is very large. Therefore, entropy is inversely proportional to GLCM energy.

Contrast is a difference moment of the P and it measures the amount of local variations in an image [1].

Inverse difference moment measures image homogeneity. This parameter achieves its largest value when most of the occurrences in GLCM are concentrated near the main diagonal. IDM is inversely proportional to GLCM contrast [2], [4].

Energy	$\sum_i \sum_j P_d^2(i,j)$
Entropy	$-\sum_i \sum_j P_d(i,j) \log P_d(i,j)$
Contrast	$\sum_i \sum_j (i-j)^2 P_d(i,j)$
Inverse Difference Moment	$\sum_i \sum_j \frac{P_d(i,j)}{\lvert i-j \rvert^2}, i \neq j$

Table 1: Features extracted from gray level co-occurrence matrix

3 TESTING DATABASE

3.1 Description of the Test Set

The original testing material consists of 168 rock texture images from collection of Insinööri-toimisto Saanio&Riekkola Oy. The images in the database are divided into 7 different categories, each containing 24 distinct images. One image from each class can be seen in Figure 1.

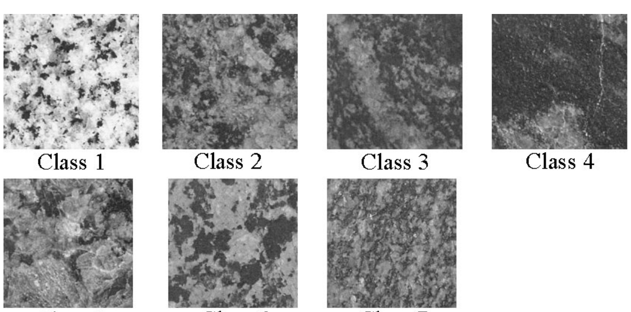

Figure 1: Rock texture classes

3.2 Normalization of the Test Set

Before computing the co-occurrence matrices the images in the database are normalized. The idea is to overcome the effects of monotonic transformations of the true image gray levels caused by variations of lightning, lens, film and digitizers. Normalization is done for all the images in the database by setting mean and standard deviation to common values.

3.3 Splitting of the Images

Apparently some of the images do not contain only one texture (especially class 4). Therefore, each of the original images is divided into 9 sub images resulting in a database, which consists of 1512 images (216 images from each class). Retrieval results were produced for both original and split database.

4 EXPERIMENTS

4.1 Retrieval Procedure

This CBIR (content based image retrieval) system consists of two major parts. The first one is feature extraction, where a set of features is generated to represent the content of each image in the database. The second task is similarity measurement, where a distance between the query image and each image in the database is computed using their feature vectors so that the N most similar images can be retrieved. The block diagram of the system is presented in Figure 2.

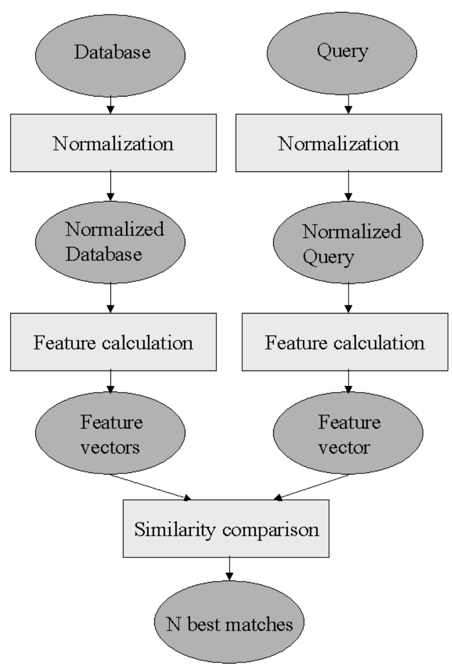

Figure 2: Block diagram of the system

Co-occurrence matrices are calculated for all the images in the normalized database. GLCM is build by incrementing locations, where certain gray levels i and j occur distance **d** apart from each other. To normalize GLCM, its values are divided by total number of increments.

Features energy, entropy, contrast and inverse difference moment are calculated from each co-occurrence matrix and their values are saved in the feature vector of the corresponding image. In order to avoid features with larger values having more influence in the cost function (Euclidean distance) than features with smaller values, feature values inside each feature class are normalized in the range [0,1].

The similarity between images is estimated by summing up Euclidean distances between corresponding features in their feature vectors. Images having feature vectors closest to feature vector of the query image are returned as best matches.

4.2 Retrieval results

The distance parameter can be optimized for each texture type based on the size of textural elements [6]. However, our testing database consists of images having different sized textural elements, and therefore, a common distance parameter is rather difficult to find. Retrieval results shown in this section are produced using the distance vector **d**=[1,1], since it takes better into consideration also textures containing small textural elements.

The experiments described in this section were conducted as follows: each image is extracted from the database and considered as a query image. For each query image 20 best matches were retrieved from the database. Ideally the goal is to have all the retrieved query images belonging to the same class as the query.

Overall percentage of best matches coming from certain class is shown in Table 2 and Table 3. Table 2 shows the results for normalized whole rock images, while Table 3 represents the results for normalized split rock images.

C1	C2	C3	C4	C5	C6	C7
100.0%						
	41.7%	5.4%	21.9%	16.2%	10.2%	4.6%
	10.0%	64.6%	20.0%		5.4%	
	19.8%	16.3%	29.4%		3.9%	30.6%
	16.3%			73.9%	9.8%	
	9.8%	1.0%	3.8%	15.4%	70.0%	
	0.2%		12.7%			87.1%

Table 2: Retrieval results for whole rock images

C1	C2	C3	C4	C5	C6	C7
100.0%						
	48.3%	4.1%	19.6%	8.5%	12.6%	6.9%
	3.3%	82.7%	13.9%		0.1%	
	19.8%	15.4%	47.1%		2.6%	15.1%
	9.9%			78.1%	12.0%	
	11.8%	0.4%	2.4%	13.4%	71.9%	0.1%
	6.1%		6.2%			87.7%

Table 3: Retrieval results for split rock images

4.3 Evaluation of the results

As can be seen from Table 2 the retrieval results especially for class 1, but also for classes 3, 5, 6 and 7 are quite reasonable. However, problems occur when considering classes 2, and particularly class 4. Main reason for this might be that some images inside these classes contain large areas of some other texture. To reduce this problem original images are divided into 9 blocks and the retrieval procedure is applied for them. Since these blocks usually consist of one texture, visual appearance of the retrieval results is better. Retrieval results for block 03_15_05 can be seen in Figure 5. Table 3 suggests that overall percentages of retrieval results from the correct class are slightly better for blocks than for the whole images.

4.4 Comparison with Gabor results

Performance of co-occurrence matrices was compared to that of Gabor wavelet features [11], which enable simultaneous localization of energy in both spatial and frequency domains. Although the upper and lower central frequency parameters U_h and U_l as well as the number of scales and orientations of the Gabor filter were chosen to be suitable for the rock image database, retrieval percentages (Table 4) were considerably lower than those for co-occurrence matrices (Table 3).

C1	C2	C3	C4	C5	C6	C7
48.4%	14.4%	11.0%		13.3%	12.7%	0.2%
13.1%	29.8%	17.7%	11.7%	9.8%	6.2%	11.7%
9.8%	22.5%	30.9%	8.7%	8.5%	9.6%	10.0%
0.4%	13.9%	8.8%	65.4%	1.7%	0.4%	9.4%
12.9%	10.3%	6.0%	1.0%	40.2%	29.6%	
12.7%	6.0%	6.9%	0.2%	33.1%	41.1%	
0.4%	11.9%	9.8%	4.6%		0.2%	73.1%

Table 4: Retrieval results for split rock images using Gabor filters

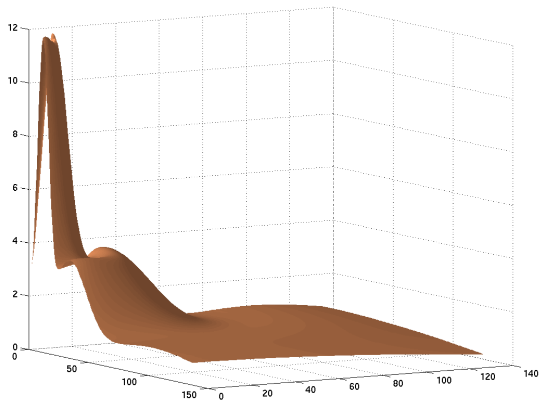

Figure 3: FFT of the Gabor filter, using Ul=0.02, Uh=0.2, 3 scales and 2 orientations

The impropriety of the Gabor filters for this particular application might result from the fact that frequency characteristics of different rock classes were quite similar and no significant directionality exist in the rock samples. Figure 3 shows the FFT of the gabor filter using parameters, which were chosen to be suitable for rock images. From Figure 4 can be seen that the FFTs of the images from class 1 and class 3 are not very clearly distinguishable.

5 CONCLUSIONS

It is known that co-occurrence matrix approach is an effective method in classifying homogeneous stochastic textures [7]. However, the results of this study indicate that co-occurrence matrix approach is also an effective method in similarity evaluation of rock textures. As can be seen from the query example with split rock images, reasonably good results were obtained when the texture is almost homogeneous. In the case of images containing multiple textures, texture segmentation should be applied before the computation of features.

6 REFERENCES

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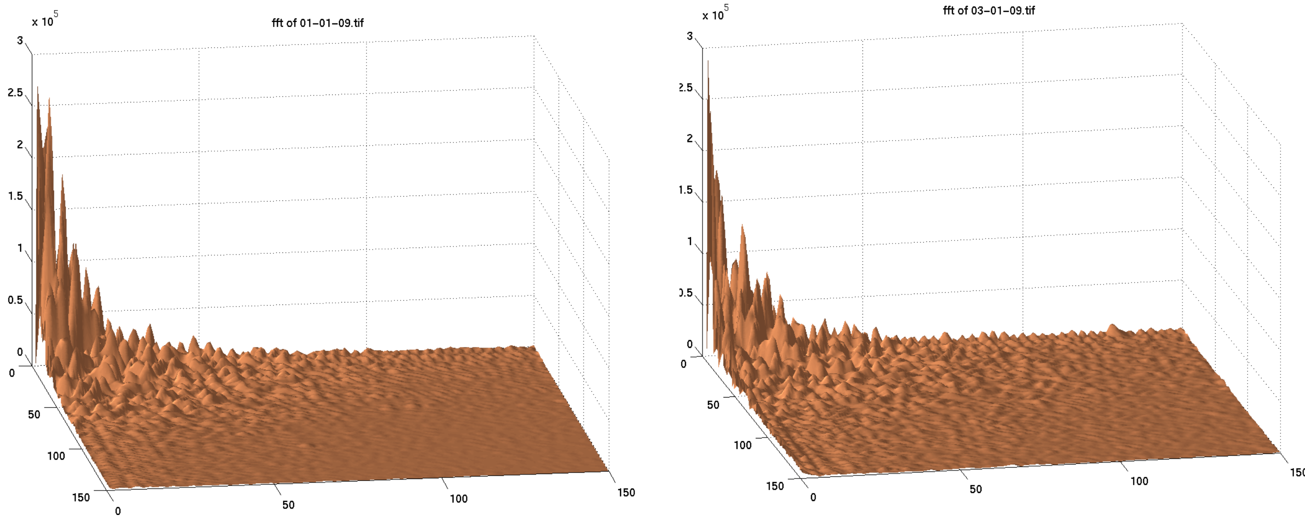

Figure 4: FFTs of the images 01_01_09.tif and 03_01_09.tif

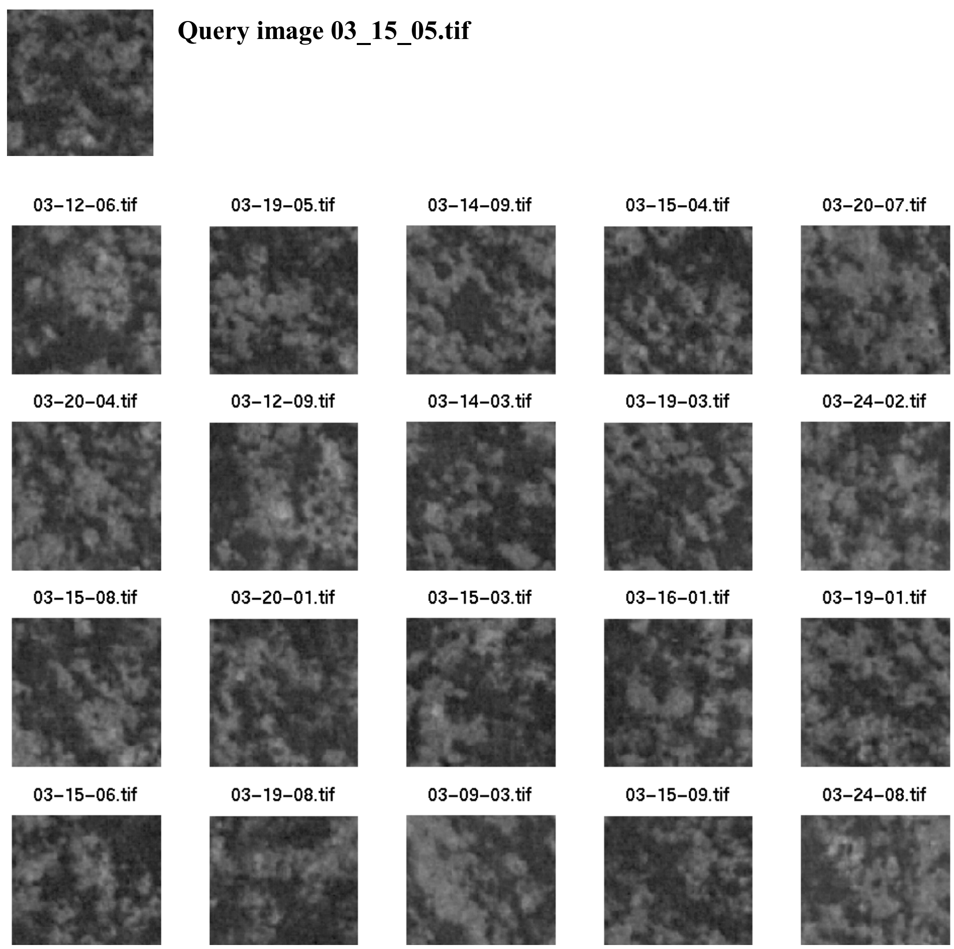

Figure 5: Retrieval results for image 03_15_05.tif