In this paper we consider the image retrieval problem. In the image retrieval the database indexing is based on some features, which are extracted from the images. In the feature extraction the image segmentation is commonly used. In the image database indexing we use a new second order statistical measure, which is based on the gray level co-occurrence matrix. The method is based on the footprint distribution of the matrix and it is called binary co-occurrence matrix. Image retrieval is made by calculating the similarity between the matrices. The main advantage of this method is that no image segmentation is needed. We test the recall ability of the binary co-occurrence matrix using a set of real paper defect images. The results are compared to the results obtained from the histogram-based retrieval. The experiments show that the binary co-occurrence matrix is a powerful tool in the image database indexing and retrieval.

1. INTRODUCTION

Image retrieval from the large databases has been object of an intensive research work during past ten years. Many methods have been developed for image retrieval and the methods are usually based on some features which are extracted from the image. In feature extraction image segmentation [3] is a common approach.

In our research work we are concentrating on the paper surface images. The objects in the images are typical paper surface defects whereas the image background is the paper surface, which forms a relatively constant distribution. Until now the analysis of paper defects has based on image segmentation [7] that is a relatively time consuming process. Therefore there is a need for a method which is able to classify the defect images without segmentation.

A gray level co-occurrence matrix is a second order statistical measure introduced by Haralick [6]. A number of measures have been developed based on it, and they have proved to be useful in texture analysis and classification [6],[11]. The co-occurrence matrix can be applied also to the image classification for retrieval purposes. In this paper we introduce an approach to that purpose: A binary co-occurrence matrix which represents the footprint of the original co-occurrence matrix.

Image histogram is a commonly used measure in the image retrieval and indexing. It is used in several content-based image retrieval applications, for example in QBIC [5] and many others [9]. In these applications histogram-based retrieval is usually based on non-segmented images and therefore we compare the retrieval ability of our approach to the results obtained from the histogram-based image retrieval. The principle of co-occurrence matrix and its binary form are presented in section two. In the retrieval the similarity between the binary matrices can be measured using a binary similarity measure, which is presented in the end of the section. In the section three we make experiments using real paper surface images. The purpose of the experiments is to find out, how well the proposed method is able to distinguish between different paper defect classes. In this part we make the comparison to image histograms. The results of the experiments are discussed in section four.
2. CO-OCCURRENCE MATRIX IN IMAGE CLASSIFICATION

Second order statistical measures, like the gray level difference histogram and the spatial gray level co-occurrence matrix [6],[11], have been popular in texture analysis during the last decades. Both of the methods are based on the gray level differences in the image.

Spatial gray level co-occurrence matrix is based on the estimation of second-order joint probability density functions $g(i,j|d,\Theta)$. Each $g(i,j|d,\Theta)$ is the probability of going from gray level $i$ to level $j$, when the intersample spacing is $d$ and the direction is $\Theta$. These probabilities create a matrix $M(i,j|d,\Theta)$ [11]. In texture analysis the matrix is usually utilized by computing some statistical measures from it [6].

2.1. Binary co-occurrence matrix

Statistics extracted from the co-occurrence matrix are not optimal for the image classification or retrieval without image segmentation. Main reason for that is the effect of the image background. The background causes a high peak to the co-occurrence matrix (figure 1b), in comparison with the object which occurs as relatively small values in the matrix. When the co-occurrence matrices of different images are compared e.g. by calculating distances between them, the peak caused by the background dominates the resulting distance. Consequently the small values of the matrix, which are the most important ones, do not have significant effect on the comparison. For that reason the matrix itself does not work as a classifying feature between the images very well. Therefore there is a need for a solution that could ignore or minimize the effect of the image background in defect classification.

Because the object in the image is represented by the small values they should be extracted from the matrix in some way. On the other hand, the contributions of the background to the matrix elements are impossible to separate from those of the defect. The simplest solution is to consider each occurrence in the matrix equally. This can be made by quantizing the values of the co-occurrence matrix into two classes, “zero” and “non-zero” values. As a result we obtain a binary matrix, which represents the footprint of the co-occurrence matrix (figure 1c). Due to its binary nature, we call the result the binary co-occurrence matrix.

2.2. Similarity measurement of the binary co-occurrence matrices

Because there is a visible similarity between the binary matrices of similar objects, the objects that belong to the same class can be found by seeking similar binary matrices among the images. In many cases it is reasonable to decrease the number of image gray levels from 256 to for instance 64 or 32. In that way the size of the co-occurrence matrix is reduced and consequently similarity measurement between the matrices will become computationally lighter. However, according to our experiments, this quantization does not significantly impair the retrieval accuracy.
The shapes of footprints can be matched by calculating similarity or distance measure between the matrices. Many different types of distance measures for similarity measurement have been developed [2],[4]. For binary data, we can count the number of elements, which contain the same or different values. When comparing two binary matrices, $B_1$ and $B_2$, let $n_{1,1}$ denote the number of the elements, whose value is 1 in both matrices. In a similar way, $n_{1,0}$, $n_{0,1}$ and $n_{0,0}$ denote numbers of matrix elements, which have values 1 and 0, 0 and 1, 0 and 0, respectively. Jaccard coefficient [4], is popular similarity measure for binary data. This coefficient is defined as:

$$S_J = \frac{n_{1,1}}{n_{1,1} + n_{1,0} + n_{0,1}}$$

3. EXPERIMENTS

The goal of the experimental part of this work is to clarify, how well the methods introduced in the section 2 can distinguish between the defect image classes. We compare the results with those of image histogram, which is a commonly used approach in image retrieval. In the histogram-based image retrieval, we use a common similarity measure, histogram intersection, introduced by Swain and Ballard [10]:

$$HIS = 1 - \sum_{i=1}^{N} \min(H1_i, H2_i)$$

in which $N$ means the number of bins in the histograms $H1$ and $H2$.

3.1. Test set

For testing purposes we had a set of real paper defect images. The images were taken from paper web using a paper inspection system [8]. The objects in the images were typical paper surface defects. The test set consisted of 1308 paper defects, which represented 14 defect classes so that each class consisted of 32-100 defect images. The images had 256 gray levels and their size had strong variations (dimension of image varied from 100 to 2000 pixels). An example image of each class and the binary co-occurrence matrix calculated from it are presented in figure 2. The co-occurrence matrix was calculated for each defect image. In calculation, intersample spacing $d$ was chosen to be one in horizontal direction. After that the co-occurrence matrices were binarized.

3.2. Retrieval experiments

The retrieval experiments were made using leaving one out method [4]. In this method each image in turn is left out from the test set and used as a query image, whereas the other images in the test set form a testing database. The performance of the retrieval was measured by calculating a precision versus recall curve [1] for each 1308 query. If $|A|$ is the number of all retrieved images, $|R|$ is the
number of query class images in the whole testing database and \(|Ra|\) is the number of retrieved query class images, precision and recall can be defined in the following way [1]:

\[
\text{Precision} = \frac{|Ra|}{|A|} \quad \text{(3)}
\]

\[
\text{Recall} = \frac{|Ra|}{|R|} \quad \text{(4)}
\]

The retrieval experiments were made using 16 and 32 gray level images. Figure 3 presents an average performance of the retrieval using binary co-occurrence matrices. These results are compared with the results obtained from retrieval based on the 256-gray level histogram. In figure 4 the average retrieval result is presented in each defect class.

4. RESULTS AND DISCUSSION

The method presented in this paper, the binary co-occurrence matrix, is a new way to retrieve images without segmentation. The main advantage of the method is that it minimizes the effect of image background. Therefore also small details of the object are visible in the distribution of the binary matrix.

In our research in the field of paper surface defects, we have noticed that the binary co-occurrence matrix is able to distinguish between the objects on the paper surface very well. The shape, size, and location of the matrix distribution are similar within each defect class, and therefore the binary matrix can be utilized in defect classification. Paper surface defects, whose classification is a very demanding task, were used as testing images. The size of the database, 1308 images, was sufficient for proper retrieval experiment. The results showed that binary co-occurrence matrix is suitable for indexing this kind of image database. Despite the fact that differences between the defect classes are in some cases

![Graph showing performance comparison](image-url)
Figure 4. An average retrieval performance of the 32 gray level binary co-occurrence matrix compared to 256 gray level histogram in terms of precision (%) versus recall (%) in each defect class.
very small. As figure 4 shows, the classes 5, 10, and 11 for example, are difficult ones. However, precision is near 100% in the classes 1, 9, and 13.

The retrieval ability of the binary co-occurrence matrix was compared to a commonly used image indexing method, image histogram. The average results presented in figure 3 show that the retrieval based on the binary co-occurrence matrix gives clearly better result. Figure 4 shows that despite the classes 4, 7, and 8, the binary co-occurrence matrix gives better retrieval result than the histogram. In general, the drawback of the histograms is that they ignore the spatial relationship of the image gray levels.

The fact that limits the use of the binary co-occurrence matrix in the image retrieval is its size, which is proportional to computational cost in image indexing and retrieval. When the number of the image gray levels is $G$, the size of the binary co-occurrence matrix is $G^2$. In the case of the histogram, the size is only $G$. On the other hand, figure 3 shows that the retrieval performance of the 16 gray level binary co-occurrence matrix is still significantly better than in case of the 256 gray level histogram (although both have the same size).

In this paper we have showed that the binary co-occurrence matrix is a useful measure in the paper surface image indexing and retrieval. The principles presented here can also be generalized to other similar image retrieval problems. When the binary co-occurrence matrix is used, image segmentation can be avoided.

5. ACKNOWLEDGMENT

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6. REFERENCES