TEXTURE SIMILARITY EVALUATION USING ORDINAL CO-OCCURRENCE

Mari Partio, Bogdan Cramariuc and Moncef Gabbouj

Tampere University of Technology, Institute of Signal Processing
P.O. Box 553, Tampere, Finland
mari.partio@tut.fi

ABSTRACT

Co-occurrence matrices have been successfully used in texture analysis. However, due to noise and monotonic shifts in gray levels, traditional co-occurrence analysis may lead to erroneous results. Using the order of the gray values instead of the gray values themselves is shown to improve the retrieval accuracy. Ordinal measures have been used for many image processing tasks in the literature. In this paper, we propose a novel combination of ordinal measures and co-occurrence matrices using local pixel pair comparisons. Features constructed in this paper represent the occurrence frequency of certain ordinal relationships at different distances and orientations. The proposed method gives encouraging results when comparing its retrieval performance to that of the traditional gray level co-occurrence matrices.

1. INTRODUCTION

Texture evaluation is needed in various applications ranging from industrial applications to medical imaging. Co-occurrence matrices, and their binary versions [5], have been successfully applied in texture analysis [7, 12]. However, due to noise and monotonic shifts in grey levels, co-occurrence matrix analysis may lead to erroneous results. This problem could be alleviated by using the order of the gray values instead of the actual pixel values.

Ordinal measures, which are based on the relative order of the pixel values, have been used in many image processing tasks in the literature. An ordinal framework for shape comparison has been introduced in [1]. Also several ordinal methods for texture description have been proposed in [3-4, 6, 8-11]. In [4] a so called texture unit (TU) is introduced. There the texture information is collected from a 3x3-neighborhood. Each neighbor of the center pixel is assigned a label 0, 1, or 2, depending on whether its value is below, equal, or above the value of the center pixel. The resulting texture units are collected into feature distribution, called texture spectrum (TS), which is used to describe the texture.

In local binary pattern approach [6, 10] a local neighborhood is thresholded at the gray value of the center pixel into a binary pattern. The final texture feature is the histogram of the operator outputs accumulated over the texture sample.

N-tuple methods consider N arbitrary neighbors of the current pixel. In [8] oriented N-tuple operators with globally thresholded binary images have been used. Later this method has been extended to gray level images and rank coding has been used to reduce the dimensionality of the features [9].

This paper proposes a novel combination of ordinal measures and co-occurrence matrices. Retrieval performance of the proposed method is evaluated using a set of well known Brodatz textures [2].

2. ORDINAL CO-OCCURRENCE

2.1. Proposed method

The proposed method produces a set of textural features, which are entirely based on the ordinal relationship between the pixels in the textured area T. Pixel pairs are used as the basic elements to construct the features. More complex pixel combinations could be used, but those are beyond the scope of this paper.

The constructed features represent the occurrence frequency of certain ordinal relationships ("greater", "equal", "smaller") at different distances D and orientations O. Because we deal with pairs of pixels, there are three possible relations, which are represented in the form of three ordinal co-occurrence matrices cooc11, cooc10, and cooc01. Each of the matrices is of size N_D*N_O, where N_D is the number of distances and N_O the number of orientations. Cooc11(D,O) represents the occurrences of current pixel C being equal to its neighbor at distance D and orientation O. Respectively, matrices cooc10(D,O) and cooc01(D,O) represent the occurrences of C being greater or smaller than its neighbor at (D, O). Based on the comparison between the pixel values, the corresponding cell in the corresponding matrix will be incremented, as shown in Figure 1. The obtained co-occurrence matrices are used to characterize the texture.

0-7803-8554-3/04/$20.00 ©2004 IEEE.

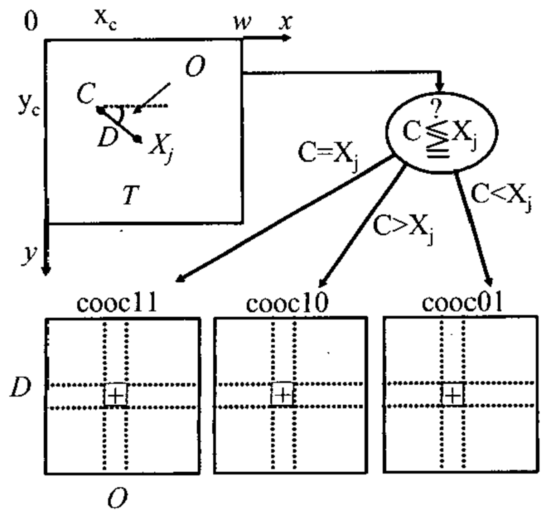

Figure 1 Incrementing ordinal co-occurrence matrices

2.2. Algorithm

The implementation of the proposed method is based on going through all N_T pixels in the textural region T, which can be of any shape. The processing is done using a neighborhood NH_C, whose size depends on the number of used distances N_D.

$$NH_C = \{ P_i \mid D = dist(P_i, C) \le N_D \}, i = 1, \ldots, N_T$$

In order to consider all pixel pairs in T exactly once and in a predetermined manner, only the set of anti-causal neighbors X of the current pixel C is considered.

$$X \subset NH_C,$$
$$X = \{ P_i \mid D = dist(P_i, C) \le N_D \text{ and } off(P_i) > off(C) \},$$
$$off(C) = y_C \cdot w + x_C$$

where P_i, C are pixels, $off(C)$ is the offset of the current pixel, w is width of the region T, x_c and y_c are the coordinates of the current pixel. We denote by X_j the elements of the set X.

For example if we consider $N_D = 1$, then $NH_C = \{X_{-4}, X_{-3}, X_{-2}, X_{-1}, X_1, X_2, X_3, X_4\}$ and $X = \{ X_1, X_2, X_3, X_4 \}$ as shown in Figure 2.

X_{-4}	X_{-3}	X_{-2}
X_{-1}	C	X_1
X_2	X_3	X_4

Figure 2 3x3 neighborhood of pixel C

The following pseudo code describes the algorithm for building the ordinal co-occurrence matrices.

```
1.   FOR all pixels in T
2.      Set current pixel C
3.      FOR all anti-causal neighbors Xj of C
4.         IF (Xj inside T)
5.            Determine D and O
6.            Increment all_cooc(D,O)
7.            IF ( C = Xj )
8.               Increment cooc11(D,O)
9.            ELSEIF ( C > Xj )
10.              Increment cooc10(D,O)
11.           END
12.        END
13.     ENDFOR
14.  ENDFOR
15.  Normalize cooc11 and cooc10 with all_cooc
```

Results are saved in the form of ordinal co-occurrence matrices, which are incremented based on the values and spatial relationships of the current pixel and its neighbors. All occurrences of distance and orientation patterns are saved in matrix all_cooc for normalization purposes. If current pixel C is equal to the considered neighbor X_j, the matrix cooc11 is incremented. On the other hand, if C is greater than X_j, the matrix cooc10 is incremented. We could also consider a third relation were C is smaller than X_j. However, this information could also be obtained from cooc11, cooc10 and all_cooc matrices. The obtained ordinal co-occurrence matrices, cooc11 and cooc10, are used as features for the considered textural region.

The number of used distances and orientations can be selected. To enable comparison of ordinal co-occurrence matrices obtained from varying texture sizes, the obtained ordinal co-occurrence matrices are normalized by the total number of pairs with the corresponding distance and orientation when moving over the region T. The normalization is performed at step 15 in the algorithm.

2.3. Feature comparison

Matrices are compared using city-block distance. The total difference between two textural regions T_1 and T_2 can be obtained by summing up the differences from the matrix cooc11 and cooc10 comparisons. We assume that same number of distances and orientations are used for both textural regions.

$$dist(T_1, T_2) = \sum_{i,j} \left| cooc11_{T_1}(i,j) - cooc11_{T_2}(i,j) \right| + \sum_{i,j} \left| cooc10_{T_1}(i,j) - cooc10_{T_2}(i,j) \right|$$

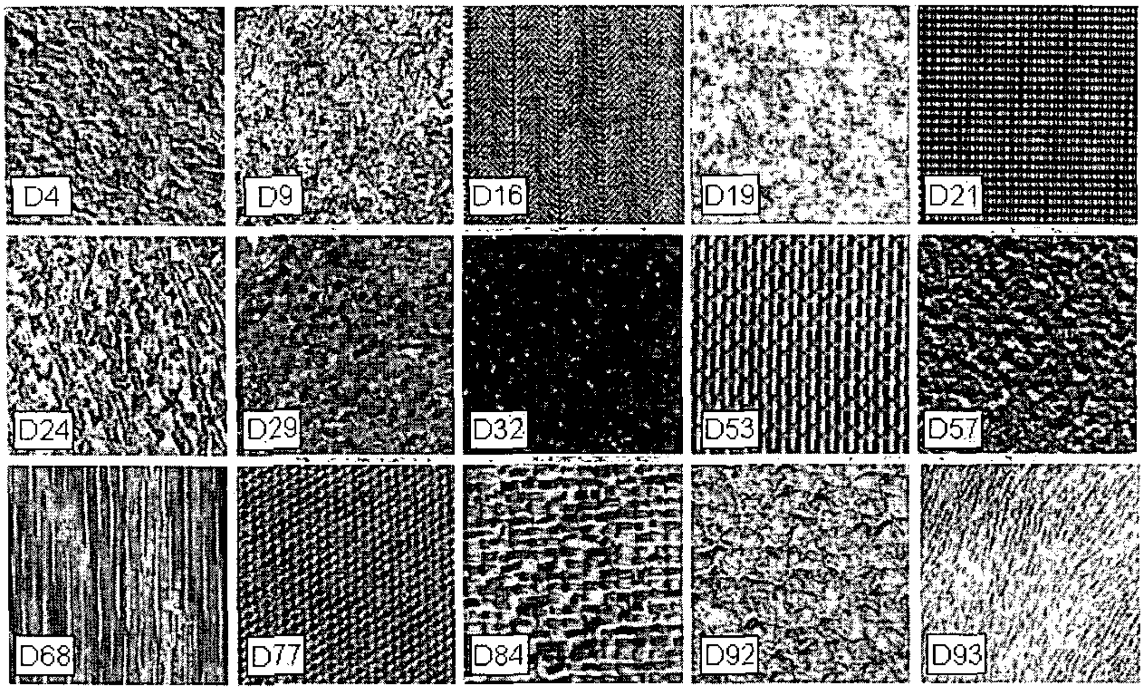

Figure 3 Samples of Brodatz textures

3. RESULTS

3.1. Test database

In the retrieval experiments, we used 15 classes of Brodatz textures [2]. The selected classes are the same as were used in [10], but now the images are not globally gray scale corrected. Each of the original images is split into 16 pieces of size 160x160, resulting in a database with 240 images. One sample from each class is shown in Figure 3. Before the experiments images in the test database are uniformly quantized into 32 gray levels.

3.2. Experiments

All retrieval results shown in this paper are obtained using ordinal co-occurrence method with 5 distances and 4 orientations. Since the database contains 16 samples from each of the classes, 16 best matches in retrieval are considered. Each row in Table 1 corresponds to retrieval results for one sample from each class in retrieval order using the ordinal co-occurrence approach. Gray area corresponds to samples retrieved from the correct class. For example, in the second row of Table 1 we can see that for one sample of class D4, 15 out of 16 samples are correctly retrieved and that the only incorrectly retrieved sample occurs in the 16^{th} position. To be more complete, we used each image from each class as a query image and calculated the number of correct matches during retrieval. The average numbers of correct matches for each class using ordinal co-occurrence method are represented in second last column of Table 1. For comparison purposes, the last column of Table 1 shows the average number of correct retrievals for gray level co-occurrence matrices (GLCM) [12].

3.3. Evaluation of the results

As can be seen in Table 1, most of the classes are retrieved correctly using the ordinal co-occurrence approach. For some classes the retrievals are mixed with some images from other classes. However, in most of those cases, the closest matches are retrieved correctly and the errors occur towards the end of the list of best matches. For some of the classes, especially for D19, the retrieval performance of GLCM seems to be slightly better than that of ordinal co-occurrence matrices. This may be due to the fact that those textures contain relatively large areas with slightly varying gray levels causing some variations in ordinal co-occurrence matrices. However, Table 1 suggests that the overall retrieval performance of the proposed ordinal co-occurrence matrices is better than the retrieval capability of traditional gray level co-occurrence matrices.

Query rank	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	Ord	GLCM
D4	D4															D9	15.13	15.00
D9	D9									D24	D9		D4	D9	D4	D24	11.69	5.90
D16	D16																16.00	8.70
D19	D19											D29	D19	D29			11.88	15.00
D21	D21															D57	14.88	16.00
D24	D24							D9	D24			D9	D24	D9			10.94	7.80
D29	D29															D19	14.75	14.00
D32	D32															D29	13.81	16.00
D53	D53																16.00	7.40
D57	D57																16.00	14.00
D68	D68														D19		13.75	11.00
D77	D77																16.00	9.00
D84	D84																16.00	16.00
D92	D92														D4	D9	14.13	14.00
D93	D93										D24	D9	D93	D9		D24	10.75	9.80
Average																	14.1	12.0

Table 1 Example retrieval results

4. CONCLUSIONS

We presented a novel combination of ordinal measures and co-occurrence matrices. The proposed method can be used to characterize texture based on ordinal relations between pixels. The method was shown to perform well for retrieval purposes using a set of Brodatz images. The average retrieval capability of the proposed method was also better than that of the traditional co-occurrence matrices. Although the used simple comparison method produced encouraging results, better results might be obtained if more sophisticated comparison method would be applied. Increasing the spatial predicate D allows to generalize this method to any neighborhood size. The optimal value for D depends on the texture in question.

5. ACKNOWLEDGMENTS

Financial support provided by Graduate School in Electronics, Telecommunications and Automation (GETA) is gratefully acknowledged.

6. REFERENCES

[1] F. Alaya Cheikh, B. Cramariuc, M. Partio, P. Reijonen, and M. Gabbouj, "Ordinal-Measure Based Shape Correspondence", *Eurasip Journal on Applied Signal Processing*, vol. 2002, no. 4, April 2002, pp. 362-371.

[2] P. Brodatz, Textures: A Photographic Album for Artists and Designers, Dover Publications, New York, 1966.

[3] Y. Q. Chen, M.S. Nixon, and D.W. Thomas, "Statistical Geometrical Features for Texture Classification", *Pattern Recognition*, vol. 28, no. 4, 1995, pp. 537-552.

[4] D. - C. He, and L. Wang, "Texture Unit, Texture Spectrum, and Texture Analysis," *IEEE Trans. on Geoscience and Remote sensing*, vol. 28, no. 4, pp. 509–512, July, 1990.

[5] I. Kunttu, L. Lepistö, J. Rauhamaa, and A. Visa, "Binary co-occurrence matrix in image database analysis", *Proc. of the 13th Scandinavian Conference on Image Analysis, SCIA 2003*, Halmstad, Sweden, 29th June – 2nd July 2003, pp. 1090-1097.

[6] T. Ojala, M. Pietikäinen, "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 24, No. 7, July 2002.

[7] M. Partio, B. Cramariuc, M. Gabbouj, and A. Visa, "Rock Texture Retrieval using Gray Level Co-occurrence Matrix", *NORSIG-2002, 5th Nordic Signal Processing Symposium*, On Board Hurtigruten M/S Trollfjord, October 4-7, 2002, Norway.

[8] D. Patel, and T.J. Stonham, "A Single Layer Neural Network for Texture Discrimination", in *Proc. IEEE International Symbosium on Circuits and Systems*, 1991, pp. 2657-2660.

[9] D. Patel, and T. J. Stonham, "Texture image classification and segmentation using RANK-order clustering," in *Proc. 11th International Conference on Pattern Recognition*, vol.3, 30th Aug- 3rd Sep. 1992, pp. 92-95.

[10] M. Pietikäinen, T.Ojala and Z. Xu, "Rotation-invariant Texture Classification using Feature Distributions", *PatternRecognition*, Vol. 33, Issue 1, January 2000, pp. 43-52.

[11] M. Singh, and S. Singh, "Spatial Texture Analysis: A Comparative Study", in *Proc. 16th International Conference on Pattern Recognition*, vol. 1, 11th-15th Aug 2002, pp. 676-679.

[12] J. S. Weszka, C. R. Dyer, and A. Rosenfeld, "A Comparative Study of Texture Measures for Terrain Classification", *IEEE Trans. on Systems, Man, and Cybernetics*, vol. SMC-6, no. 4, April 1976.