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Texture Retrieval Using Ordinal Co-occurrence Features

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ABSTRACT

Due to variations in illumination conditions in texture evaluation applications, gray scale invariance is an important property in texture similarity evaluation. 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 thresholding. 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 rotation invariant local binary pattern approach and 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 have been successfully applied in texture analysis [1, 2]. However, due to noise and monotonic shifts in gray 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 literature. An ordinal framework for shape comparison has been introduced in [3]. Also several ordinal methods for texture description have been proposed in [4 – 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 [8, 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 [5] 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 [6]. Comparisons of *N*-tuple methods can be found in [7].

In this paper we propose 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 [12].

2. ORDINAL CO-OCCURRENCE

2.1 Proposed method

The purpose of this novel method is to produce 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.

Features are formed using a moving window *W*, size of which depends on the number of distances used. For each position of the window its content is first thresholded by the value X_O of the center pixel in the window. If the pixel value is smaller than X_O, thresholded value is 0. Otherwise the thresholded value is 1. Within the thresholded window all pixels are compared to their forwarding neighbors in a predetermined manner, which is described in section 2.2.

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 four possible relations, which are represented in the form of four ordinal co-occurrence matrices cooc11, cooc00, cooc10, and cooc01. Each of the matrices is of size N_D*N_O, where N_D means number of distances and N_O number of orientations. Cooc11(D,O) represents the occurrences of the thresholded values of current pixel *C* and its neighbor both being equal to 1 at distance *D* and orientation *O*, while cooc00(D,O) represents the similar case when both of the values equal to 0. Cooc10(D,O) shows the occurrences where the thresholded value of the

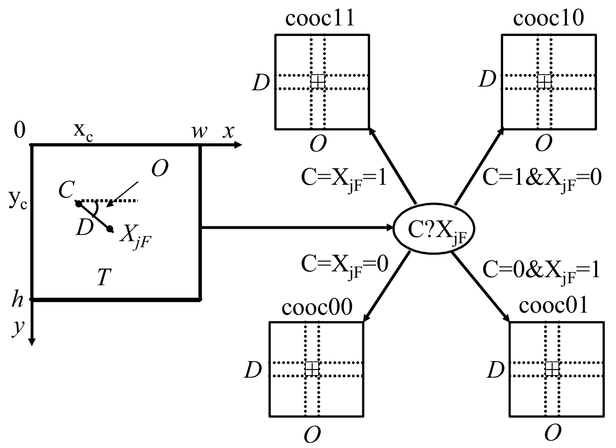

Fig. 1. Incrementing ordinal co-occurrence matrices

current pixel is 1 and value of its neighbor is 0 at (D,O). The opposite situation is represented in cooc01(D,O). Based on the comparison between the pixel values, the corresponding cell in the corresponding matrix is incremented, as shown in Fig. 1. The obtained co-occurrence matrices are used to characterize the texture.

2.2 Algorithm

The implementation of the proposed method is based on scanning all N_T pixels in the textural region T. The processing is done using a neighborhood NH_C, size of which depends on the number of used distances N_D.

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

In order to consider all pixel pairs inside each neighborhood at most once in a predetermined manner, only the set of forwarding neighbors X_F of the current pixel C is considered.

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

where P_i, C are pixels, $off(C)$ is the offset of the current pixel, w and h are the width and height of the region T, x_c and y_c are the coordinates of the current pixel. We denote by X_{jF} the elements of the set X_F. For example if we consider $N_D = 1$, then $NH_C = \{X_{1F}, X_{2F}, X_{3F}, X_{4F}, X_1', X_2', X_3', X_4'\}$ and $X_F = \{X_{1F}, X_{2F}, X_{3F}, X_{4F}\}$ as shown in Fig.2.

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

Fig. 2. 3x3 neigborhood with four center symmetric pixel pairs

```
1.    FOR all possible center positions in T
2.      Threshold the window W using threshold X0
3.        FOR all pixels C in W
4.          FOR all forwarding neighbors XjF of C
5.            Determine D and O
6.              IF ( C = 1 & XjF = 1 )
7.                Increment cooc11(D,O)
8.              ELSEIF ( C = 0 & XjF = 0 )
9.                Increment cooc00(D,O)
10.             ELSEIF ( C = 1 & XjF = 0 )
11.               Increment cooc10(D,O)
12.             ELSE
13.               Increment cooc01(D,O)
14.             END
15.           ENDFOR
16.         ENDFOR
17.     ENDFOR
18.     Normalize cooc-matrices
```

Fig. 3. Pseudo-code of the algorithm

Pseudo code presented in Fig. 3 describes the algorithm for building the four ordinal co-occurrence matrices. In the pseudo code C and X_{jF} represent the thresholded pixel values.

Number of used distances and orientations can be selected. To reduce the number of calculations, masks for distances and orientations are pre-calculated. Since the mask itself does not provide equal number of pixels for all the distances and orientations, the obtained co-occurrence matrices are normalized by the total number of pairs with the corresponding distance and orientation when moving over the region T. This normalization is performed at step 18 in the algorithm.

2.3 Feature comparison

Matrices are compared using Euclidean 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, cooc10, cooc01, and cooc00 comparisons.

$$\begin{aligned} dist(T_1, T_2) = &\sqrt{\sum_{i,j} \left(cooc11_{T1}(i,j) - cooc11_{T2}(i,j)\right)^2} + \\ &\sqrt{\sum_{i,j} \left(cooc10_{T1}(i,j) - cooc10_{T2}(i,j)\right)^2} + \\ &\sqrt{\sum_{i,j} \left(cooc01_{T1}(i,j) - cooc01_{T2}(i,j)\right)^2} + \\ &\sqrt{\sum_{i,j} \left(cooc00_{T1}(i,j) - cooc00_{T2}(i,j)\right)^2} \end{aligned}$$

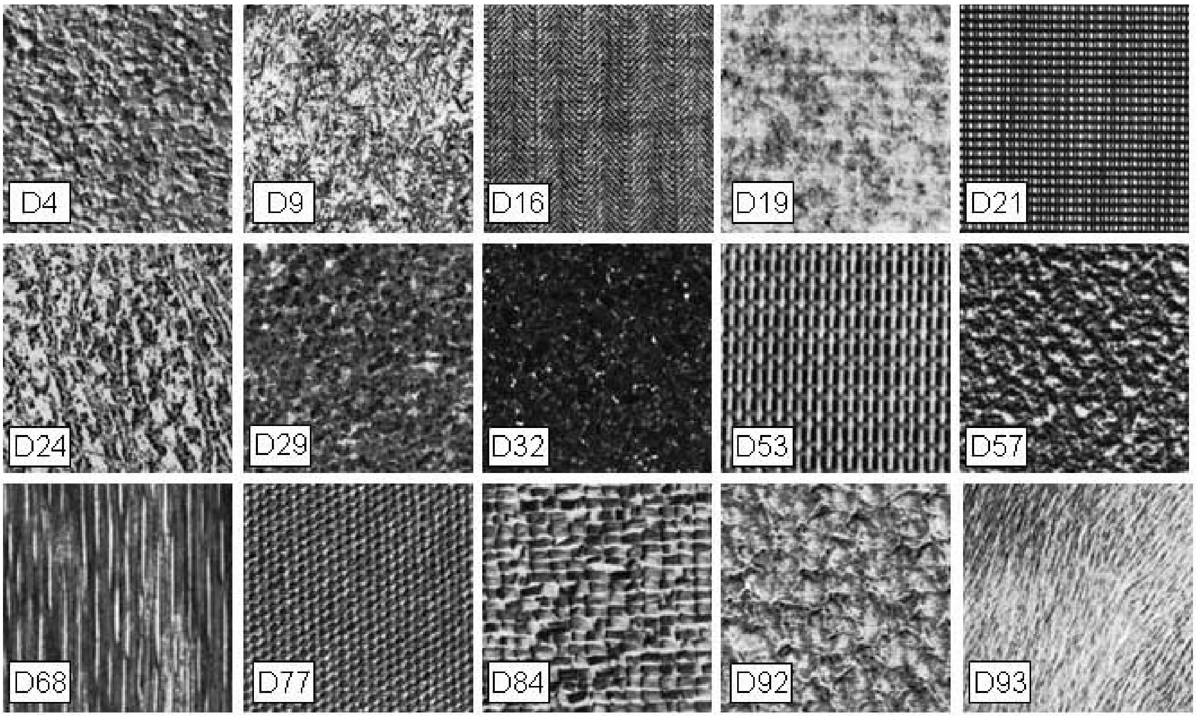

Fig. 4. Samples of Brodatz Textures

3. RESULTS

3.1 Test database

In the retrieval experiments, we used 15 classes of Brodatz textures [12]. Selected classes are the same as were used in [8], but now the images are not globally gray scale corrected. Each of the original images is split into 16 160x160 pieces, resulting to database with 240 images. One sample from each class is shown in Fig. 4.

3.2 Experiments

Retrieval results shown Table1 and Table2 are obtained using ordinal co-occurrence method with 7 distances and 4 orientations. Since the database contains 16 samples from each of the classes, 16 best matches in retrieval are considered. Retrieval results for one sample from each class using the proposed ordinal co-occurrence method are shown in Table 1 in retrieval order. For comparison purposes second last column of Table 1 shows the correct number of retrievals for gray level co-occurrence matrices (GLCM) [1] with displacement vector d=[1, 1]. Last column of the Table 1 represents the retrieval results for multiresolution rotation invariant local binary pattern operator $LBPRIU_{P,R}$ [10]. The experiments are performed using following parameter combinations for P and R (8, 1 + 16, 2 + 24, 3).

To be more complete we used each image from each class to be as a query image and calculated the number of correct matches in retrieval. The average number of correct matches for each class using ordinal co-occurrence method is represented in Table 2. As can be seen from the Table 2, example retrievals in Table 1 correspond well to the average case.

3.3 Evaluation of the results

As can be seen in the Table 1 majority of classes are retrieved correctly using the proposed ordinal co-occurrence method. For some of the classes the retrievals are mixed with some images from other classes. However, in all of those cases at least 14 closest matches are retrieved correctly and the errors occur towards the end of the list of best matches. Table 1 suggests that the retrieval performance of the proposed ordinal co-occurrence matrices is better than that of the LBPRIU and GLCM approaches. Table 2 suggests that in average case the retrieval accuracy of ordinal co-occurrence matrices resembles that shown in Table 1.

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 retrieval capability of the proposed method was also shown better than that of the traditional co-occurrence matrices and multiresolution rotation invariant local binary patterns. 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

Table 1. Comparison of the query results using ordinal co-occurrence method, GLCM, and LBPRIU

Query	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	ORD	GLCM	LBP
D4	D4																16	14	9
D9	D9														D24		14	5	9
D16	D16																16	12	16
D19	D19															D92	15	16	13
D21	D21																16	16	16
D24	D24														D9	D24	15	6	15
D29	D29																16	13	16
D32	D32																16	16	16
D53	D53																16	6	16
D57	D57																16	15	16
D68	D68																16	13	16
D77	D77																16	10	16
D84	D84																16	16	16
D92	D92															D19	15	15	13
D93	D93														D9		14	13	16
Average																	15,5	12,4	14,6

Table 2. Average number of correct matches for each class using ordinal co-occurrence, Rcc = retrievals from correct class

Query	Rcc	Query	Rcc
D4	15,6	**D53**	16
D9	14,9	**D57**	16
D16	16	**D68**	15,9
D19	14,5	**D77**	16
D21	16	**D84**	16
D24	15,2	**D92**	14,7
D29	16	**D93**	14,5
D32	15,9	**Average**	15,5

question. Future work will consider the reduction in computational complexity of the proposed method. This might be obtained by using only the most relevant pixel pairs in the comparisons.

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