Block-based Ordinal Co-occurrence Matrices for Texture Similarity Evaluation

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Abstract—**In this paper we introduce a block-based approach for ordinal co-occurrence matrices aimed at improving robustness of the basic ordinal co-occurrence. Earlier, we have introduced two approaches for building ordinal co-occurrence matrices. One considers only the center pixel of a moving window as a seed point, compares it to its anti-causal neighbors and saves the occurrences of ordinal relations between pixels in the form of co-occurrence matrices. However, in that approach problems occur especially when considering textures with slightly varying gray levels in relatively large areas. The other method improves the robustness of the earlier method by considering also other pixels than the center pixel in the thresholded window as seed points. Main drawback of that method is the increased computational complexity. In order to avoid that, a block-based approach for building the ordinal co-occurrence matrices is introduced in this paper. Retrieval accuracy of the proposed method has shown to produce better results than existing techniques.**

Keywords-texture; retrieval; co-occurrence; ordinal methods

I. INTRODUCTION

In many application domains, such as remote sensing and industrial applications, texture is affected by changes in illumination conditions. Therefore, grey scale invariance is an important property for texture features.

Several methods have considered grey-scale invariant texture features using an ordinal approach [2-4, 6-10]. N-tuple methods consider a set of N neighbors of the current pixel [3]. Due to limitations of binary texture co-occurrence spectrum (BTCS) [8] and gray level texture co-occurrence spectrum (GLTCS) [9], zero-crossings texture co-occurrence spectrum (ZCTCS) was introduced [3]. It first detects the edges and then represents them by the BTCS. Relatively good results are obtained, but the disadvantage is that the method is tuned to a particular scale of operation.

In [2] texture co-occurrence spectrum is introduced. Three possible values (0, 1, 2) can be assigned for the neighbors of the center pixel, depending on whether their value is smaller, equal or greater than the value of the center pixel. Resulting texture units are collected into feature distribution, called texture spectrum, which is used to describe the texture. In local binary pattern (LBP) approach [4, 10] a local neighborhood is thresholded into a binary pattern, which makes the distribution more compact and reduces the effect of quantization artifacts. Histogram of the operator's outputs accumulated over the texture sample is used as a final texture feature.

Earlier, we have introduced two approaches for building ordinal co-occurrence matrices [6, 7]. In [7] only the center pixel of a moving window is compared to its anti-causal neighbors. However, in that approach problems occur especially when considering textures with large areas of slightly varying gray levels. In order to improve the robustness, we consider also the other pixels in the window as seed points [6]. The main drawback of that method is the increase in computational complexity. The method presented in this paper represents a further development and combination of the two approaches. Now instead of comparing only the center pixel to its anti-causal neighbors, other pixels are also used as seed points, as is done in [6]. However, to avoid the increase in computational complexity a block-based approach for building the ordinal co-occurrence matrices is introduced. Retrieval performance of the proposed method is evaluated using a set of well known Brodatz textures [1].

This paper is organized as follows. Proposed block-based method for ordinal co-occurrence is described in section II and its complexity is evaluated in section III. Test database and experimental results are presented in section IV. Conclusions and future work are discussed in section V.

II. BLOCK-BASED ORDINAL CO-OCCURRENCE

A. Proposed Method

The proposed method, Blockordcooc, produces a set of textural features, which are entirely based on the ordinal relationship between the pixels in the textured area T. The basic idea of this paper is based on the approach presented in [6] but the computational complexity of the method is significantly reduced. The main simplification is due to adopting a block-based approach, where the thresholded window is first divided into blocks B_{xy}. The value m_{xy} for each block is determined using the majority decision. If the majority of values within the block are 1s, then the value of the block is determined to be 1 and vice versa. If an equal number of ones and zeros occur, thresholded value of the center pixel is selected. This block-based approach utilizes, instead of pixelwise comparison, relative occurrence of representative block values (m_{xy}) for constructing the feature matrices.

The constructed features represent the occurrence frequency of certain ordinal relationships ("greater", "equal", "smaller") at different distances D and orientations O. By distances we mean here inter-block distances, such that distance between two neighboring blocks is 1. Because we deal with pairs of blocks, there are four possible relations,

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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 is the number of distances and N_O the number of orientations. Cooc11(D,O) represents the occurrences of the value of current block C and its neighbor both being equal to 1 at distance D and orientation O, while cooc00(D,O) represents the corresponding case when both values equal 0. Cooc10(D,O) shows the occurrences where the value of the current block 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 block values, the corresponding cell in the corresponding matrix is incremented, as shown in Figure 1. The resulting co-occurrence matrices are used to characterize the texture.

B. Algorithm

A rectangular window W of width w_p=2*bs*N_D+bs pixels is moved over the whole textural region T one block size bs at a time. The entries are first thresholded by the value of the center pixel X_0. Processing of the thresholded window is done in a block-based manner. First W is divided into S blocks of size $bs*bs$. After combining the pixels within each of the blocks we obtain a sampled window SW of width w=2*N_D+1. Each value m_{xy} in the window SW is obtained using the majority decision inside the corresponding block B_{xy}. In order to consider all pairs of values inside SW exactly once and in a predetermined manner the current value C is compared only to its anti-causal neighbors X up to distance N_D. By anti-causal neighborhood we mean the blocks located after a given block in a raster scanning order.

$$X \subset SW,$$
$$X = \{m_{xy} \mid D = dist(m_{xy}, C) \le N_D \ and\ off(m_{xy}) > off(C)\}, \quad (1)$$
$$off(C) = y_C \cdot w + x_C$$

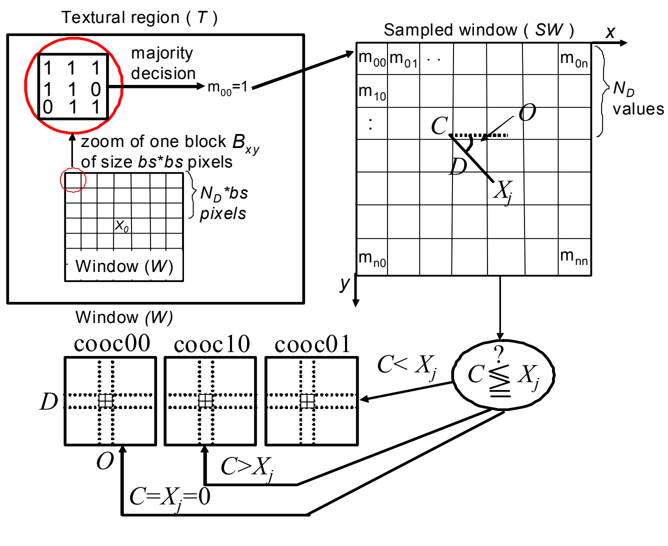

Figure 1 Construction of the ordinal co-occurrence matrices

where C is the current block value, *off(C)* is the offset of the current block, w is width of the window SW, x_c and y_c are the coordinates of the current block value within the SW window.

The pseudo code in Figure 2 describes the algorithm for building the block-based ordinal co-occurrence matrices. By X_j we denote the elements of set X.

Results are saved in the form of ordinal co-occurrence matrices, which are incremented based on the values and spatial relationships of the current block and its anti-causal neighbors. All occurrences of distance and orientation patterns are saved in matrix all_cooc for normalization purposes. Since the information of the one of the relations could be obtained from the other matrices and the all_cooc matrix, one of the matrices could be left out of the comparisons. We have selected to leave matrix cooc11 out. 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 22 in the algorithm.

C. Feature Comparison

Matrices are compared using the 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 cooc10, cooc01 and cooc00 comparisons. We assume that the same number of distances and orientations are used for both textural regions.

```
1.  FOR all possible center positions in T
2.    Threshold the window W using threshold X0
3.    FOR all blocks Bxy in W
4.      Determine block value mxy by majority decision
5.      Save the value mxy of the block in SW
6.    ENDFOR
7.    FOR all values mxy in SW
8.      LET C be the current mxy value
9.      FOR all anti-causal neighbors Xj of C
10.       Determine D and O
11.       Increment all_cooc(D,O)
12.        IF ( C  = 0 & Xj  = 0 )
13.          Increment cooc00(D,O)
14.        ELSEIF ( C  = 1 &  Xj  = 0 )
15.          Increment cooc10(D,O)
16.        ELSEIF (C = 0 & Xj = 1)
17.          Increment cooc01(D,O)
18.        END
19.      ENDFOR
20.    ENDFOR
21. ENDFOR
22. Normalize cooc-matrices
```

Figure 2 Pseudo code for building the block-based ordinal co-occurrence matrices

III. Complexity Analysis

We will here evaluate the complexity of the proposed method and compare it to the complexity of earlier ordinal co-occurrence methods [6, 7]. The evaluation is based on the number of pixel pairs taken into consideration per each pixel in T. Let us denote by β_i this number, where i represents the method. This evaluation is approximate since in the actual calculations only the pairs up to distance N_d are considered. Let us denote by P_i the number of pairs considered per one position of the window.

For the Ordcoocmult method [6]:

$$P_0 = \frac{w_p^2\left(w_p^2 - 1\right)}{2} \approx \frac{1}{2} w_p^4, \qquad \beta_0 = P_0 \approx \frac{1}{2} w_p^4, \tag{2}$$

For the Ordcooc approach [7]:

$$\beta_1 = P_1 \approx \frac{1}{2} w_p^2 \tag{3}$$

For the proposed method Blockordcooc the analysis window W is divided in blocks, and therefore $w_p = w * bs$. In this case

$$P_2 = \frac{w^2\left(w^2 - 1\right)}{2} \approx \frac{1}{2} w^4 = \frac{1}{2}\frac{1}{bs^4} w_p^4 \tag{4}$$

Due to the fact that the window is moved one block size at a time the average number of pixel pairs β_2 taken into consideration per each pixel pair in T will be:

$$\beta_2 = \frac{P_2}{bs^2} = \frac{1}{2}\frac{1}{bs^6} w_p^4 = \left(\frac{w_p}{bs^3}\right)^2 \beta_1 \tag{5}$$

It can be noted that $\beta_2 < \beta_0$ always, since $bs > 1$. It is also clear that $\beta_1 < \beta_0$, since $w_p > 1$. The relation between β_1 and β_2 is not static but it depends on bs and w_p. β_1 is identical to β_2 when

$$bs^3 = w_p \tag{6}$$

Starting from a pair of values (bs, w_p) satisfying the above condition, if w_p is increased then the complexity of Blockordcooc becomes bigger than that of Ordcooc. However, if bs is increased, then the complexity of Blockordcooc becomes lower than that of Ordcooc. From (6) we can see that if e.g. bs=2 and w_p=8, then β_1 is identical to β_2. For bs=2 from (2) and (5) we have β_0/β_2=64 from where it can be seen that the proposed method Blockordcooc is significantly less complex than Ordcoocmult.

IV. Results

A. Test Database

In the retrieval experiments, we used 60 classes of Brodatz textures [1]. Each of the original images is split into 16 160x160 pieces, producing a database with 960 images. Sample images from some of the classes are shown in Figure 3.

B. Experiments

Since the database consists of 16 images from different classes, 16 best matches are considered in the retrieval. The average results in Table I and Table II indicate the average amount of correct matches for all the classes. Results using block-based ordinal co-occurrence approach and different parameters are shown in Table I. Comparative results using other methods are provided in Table II. Ordcoocmult refers to results obtained using the approach presented in [6]. Ordcooc presents the results using approach from [7]. LBP refers to rotation invariant local binary pattern operator $LBPRIU_{P,R}$ [4], using the following parameters for P and R (8,1 + 16,2 + 24,3). ZCTCS [3] is applied using inter pixel spacing k=1. Also gray level co-occurrence matrices GLCM [11] are evaluated with displacement vector d=[1,1] for comparison purposes.

C. Evaluation of the Results

As can be seen from Table I, best retrieval accuracy for the used database can be obtained by using N_D = 3 and bs=2. Retrieval accuracy in that case is almost as good as when using Ordcoocmult, although the computational complexity is significantly reduced by adopting the block based approach. As can be seen from Table II for the other evaluated methods block-based ordinal co-occurrence seems to perform better with the exception of Ordcoocmult. Regarding the computational complexity, $\beta_1 = \beta_2$ when for example bs=2 and w_p=8. This situation is close to first row in Table I, where w_p=10. It is noticeable that with the proposed method better results than with Ordcooc can be achieved while the computational complexity is similar. Degradation of the results by the increasing distance might be explained by the increased amount of noise in matrices with bigger distances. Increasing the block size naturally also degrades the results somewhat since the amount of simplification increases.

V. Conclusions and Future Work

In this paper we presented a further development of ordinal co-occurrence matrices by adopting a block-based approach. The proposed method can be used to characterize texture based on ordinal relations between blocks. Compared to Ordcooc the robustness is improved while the computational complexity is kept at the same level. The proposed method has also shown to perform well when compared to existing methods. The proposed method could be generalized to any neighborhood size, but when considering distances N_D greater than 5 more sophisticated feature comparison methods should be considered.

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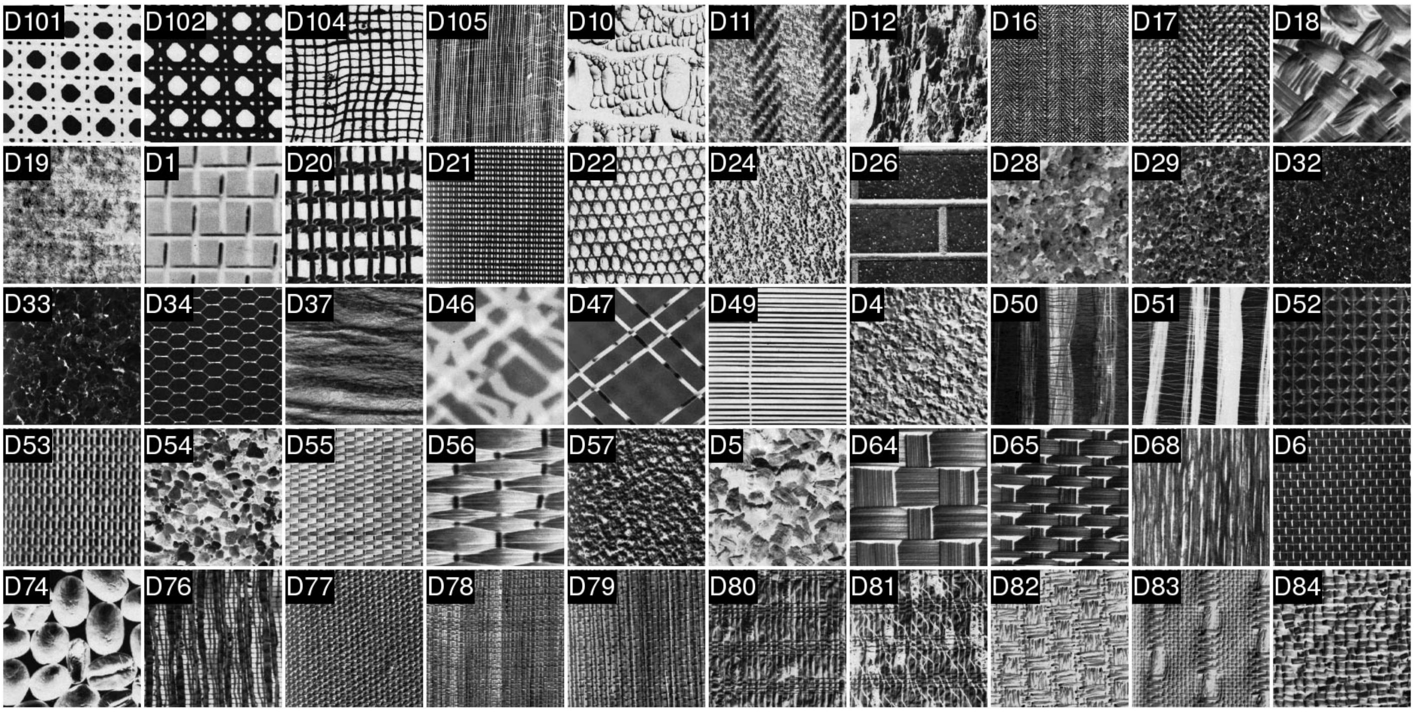

Figure 3 Samples of Brodatz textures

TABLE I. AVERAGE RESULTS FOR THE WHOLE DATABASE USING BLOCK-BASED ORDINAL CO-OCCURRENCE APPROACH

N_D	N_O	bs	Average
2	4	2	14.25
3	**4**	**2**	**14.64**
4	4	2	14.59
5	4	2	14.46
8	4	2	13.53
5	4	3	12.29
10	4	3	9.24

TABLE II. COMPARATIVE RESULTS USING OTHER METHODS

Method	Average
Ordcoocmult	14.70
Ordcooc	11.59
LBP	14.50
ZCTCS	12.59
GLCM	10.66

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