TEXTURE CLASSIFICATION BASED ON SPATIAL DEPENDENCE FEATURES USING CO-OCCURRENCE MATRICES AND MARKOV RANDOM FIELDS

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ABSTRACT

This paper presents a method for classification of textures based on features obtained from co-occurrence matrices and Markov Random Fields. Two steps are performed to classify the images. Initially, the method recognizes the homogeneous regions (object interior) in the image. Regions consisting of dissimilar elements (transition between objects) are then properly identified and classified. Experimental results demonstrate the robustness of the method in terms of variation in region size and number of parameters.

1. INTRODUCTION

Image understanding is one of the most important tasks involving a classification system. Its primary purpose is to extract information from the images to allow the discrimination among different objects of interest. The classification process is usually based on gray level intensity, color, shape, or texture. Image classification is of great interest in a variety of applications, for instance, analysis of aerial, satellite, multispectral, and medical images. In recent years, applications in content-based image retrieval systems have also been found [1].

Texture analysis forms the basis of object recognition and classification in several knowledge domains. Texture can be characterized by local variations of pixel values that repeat in a regular or random pattern on the object or image. It can also be defined as a repetitive arrangement of patterns over a region. Several methods for unsupervised and supervised texture segmentation and classification have been proposed in the literature [2, 3, 4, 5, 6]. However, neither generic methods nor formal approaches exist that are useful for a great variety of images.

Texture classification process usually involves two stages, a training step and a recognition step. In the training step, it is constructed a model for the texture content of each class in the training data, which usually is performed through labels of known classes. In the recognition step, the texture content of unknown samples is described by means of the analysis approach used in the training step. Texture features of the samples are then compared against those of the training data and the sample is assigned to that class possessing more similarity.

This work describes a method for classification of textures based on features obtained from co-occurrence matrices and Markov Random Field (MRF). The objective of the proposed classifier is to determine which regions belong to each class, given a number N of classes present in the image. Image regions are analyzed in a way that their pixels may simultaneously belong to multiple regions, then improving the results of the classification.

The paper is organized as follows. Section 2 describes the features used by the classifier. In Section 3, the proposed method is presented and discussed. Experimental results obtained by applying the classification method are shown in Section 4. Finally, Section 5 concludes with some final remarks and directions for future work.

2. TEXTURAL FEATURES

Our classifier uses the distance between the feature vector for two regions of the image to determine whether these two regions belong to a same class. Co-occurrence features and MRF features are extracted from the images, both one based on the spatial dependence of the image elements. The main aspects involving such features are described in the following two sections.

2.1. Co-ocurrence Features

A pixel is the simplest primitive that can be defined in a gray level image, whose property is its gray level intensity. Consequently, the distribution of the pixel values can be described by first-order statistics such as mean, variance and skewness, or second-order statistics such as the probability of two pixels have a certain gray level according to a particular spatial arrangement. This information can be summarized by using bidimensional co-occurrence matrices calculated for different distances and orientations.

The co-occurrence matrix is a tabulation of relative frequencies $P(i, j; d, \theta)$ with which two neighboring pixels
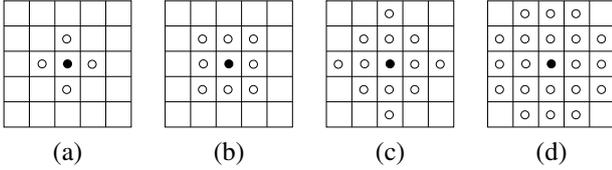
Fig. 1. Neighborhood for a central pixel. (a) first order; (b) second order; (c) third order; (d) fourth order.

Fig. 2. Example illustrating the steps of our texture classification method.

separated by distance d in a θ orientation occur on the image, one with gray level i and the other with gray level j. Such matrices of spatial gray level dependence frequencies are symmetric and correspond to a function of the angular relationship between the neighboring pixels and a function of the distance between them [7].

Each sampled region has its co-occurrence matrix calculated for $d = 1$ and $\theta = 0^o, 45^o, 90^o, 135^o$. From each matrix, fourteen statistical features [8] are extracted including variance, angular second moment, energy, contrast, correlation, homogeneity, inverse different moment, sum average, sum variance, sum entropy, difference variance, difference entropy, information measure of correlation, and maximal correlation coefficient. The average of the measurements in all four directions is used as feature values.

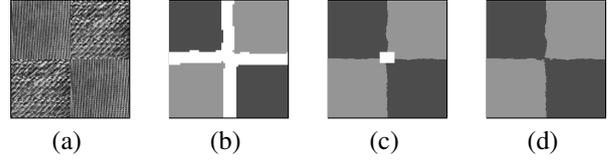### 2.2. Markov Random Field Features

In [9], Besag proposes the concept of Markov Random Fields (MRF) as a distribution of conditional probabilities over elements in a lattice, where the probability that an element assumes a certain value depends only on the values of its neighbors. In the image processing context, such concept was introduced in [10, 11, 12].

Each pixel in the image is considered as a random variable, X_r, which can assume values $x_r \in \{0, 1, \ldots, G-1\}$, where G is the number of gray levels of the image. The probability that X_r assumes the value x_r is given by the conditional probability $P(X_r = x_r|\eta_r)$, where η_r is the neighbor set for the element X_r. Figure 1 illustrates different orders of neighborhood for a central pixel.

In [9], a number of probability distribution models for MRF are presented, such as auto-normal, auto-binomial, and auto-logistic. Free parameters of the auto-logistic model were chosen as features, whose probability distribution is shown in equation 1, such that T depends on the neighborhood.

$$P(X_r = x_r|\eta_r) = \frac{e^{x_r T}}{1 + e^T} \tag{1}$$

The MRF features used by the classifier are the free parameters contained in T (details in [10]), such that the number of parameters varies according to the adopted neighborhood order. Codings' method [9] is used to obtain indepen-

dent random variables from a region to be classified. The estimation of these parameters is obtained through the maximization of loglikelihood function (equation 2), for each coding.

$$L = \sum_t \ln \left[P(X_t|\eta_t) \right] \tag{2}$$

3. PROPOSED METHOD

The developed classifier is based on the calculation of Euclidean distance between the feature vectors of a region and each class of the image to determine which class belongs to each region. The feature vector components are either the MRF parameters or the co-occurrence features described in Section 2.

Since our classification method does not include a training stage, the classes to be identified are sampled from the test images. Those classes that occur more frequently in the image are considered as *relevant classes*.

Two main steps are defined to classify the input image. The first step performs the identification of relevant classes and the classification of homogeneous regions (object interior) of the image. The purpose of the second step is to classify regions consisting of dissimilar elements (transition between objects) of the image.

3.1. Identification of Relevant Classes

Due to the fact that our method does not have a training step, it becomes necessary to generate a set of possible classes containing representative patterns of the image. Hence, regions defined as initial classes are sampled from the image. For each one of these samples is calculated the feature vector.

Once the initial classes have been determined, all regions of the image are analyzed for further classification. For each pixel, a convolution mask is repeatedly moved by 8 pixels along the image, allowing an overlap between two distinct regions. Each region is assigned to the class of the closest feature vector considering the Euclidean distance.

Since only N classes are defined by the user, but an arbitrary number of initial classes are sampled from the image, it is necessary to reduce this number until N classes are achieved. At each iteration, the initial class containing

the least number of regions assigned to it is discarded. Such regions are reassigned among the resulting classes using the Euclidean distance.

As mentioned above, an overlap of regions during the sampling process was allowed. Therefore, a pixel is classified as a certain class only if all regions under consideration containing such pixel have produced the same class as result. Pixels in homogeneous regions of the image are classified in this step, as shown in Figure 2(b).

3.2. Solving Conflicting Regions

This step is responsible for the classification of pixels located in areas of transition between classes, such as the white regions illustrated in Figure 2(b). The algorithm searches for the two possible classes which the pixel might belong to, and determines the location where the transition occurs. This procedure is repeated until all pixels in the image have been classified. Some definitions used to describe our method are presented below.

$\mathbf{v_{x,y}}$: feature vector for a mask centered at (x, y).

$\mathbf{v_{c_i}}$: feature vector that defines the class c_i.

$d(\mathbf{v_i}, \mathbf{v_j})$: Euclidean distance between vectors $\mathbf{v_i}$ and $\mathbf{v_j}$.

$P_{x,y}$: class which pixel with coordinates (x, y) belongs to.

$P_{x,y} = \emptyset$: pixel not yet classified.

$P_{x,y} = c_i$: pixel classified as class c_i.

$p_{x,y}$: pixel with coordinates in (x, y).

$\epsilon, \epsilon', \Delta, \Delta'$: integers greater than 0.

To determine two possible classes which $p_{x,y}$ will be classified to, it is assumed that the pixels not classified during the first step (section 3.1) are in regions of the image where class transitions occur.

For each $P_{x,y} = \emptyset$, if $P_{x,y+\Delta} = \emptyset$ or $P_{x,y-\Delta'} = \emptyset$, and $P_{x+\epsilon,y} = \emptyset$ or $P_{x-\epsilon',y} = \emptyset$, $P_{x,y}$ remains as $\emptyset$, i.e., the pixel is not classified in this iteration since it is not possible to identify the two classes of this region. However, if $P_{x,y+\Delta} = c_1$ and $P_{x,y-\Delta'} = c_2$ or $P_{x+\epsilon,y} = c_3$ and $P_{x-\epsilon',y} = c_4$, $p_{x,y}$ will belong to class c_1 or c_2 if $\Delta + \Delta' < \epsilon + \epsilon'$; otherwise, $p_{x,y}$ will be classified as c_3 or c_4.

Considering that $\Delta + \Delta' < \epsilon + \epsilon'$, i.e., $P_{x,y} = c_1$ or $P_{x,y} = c_2$ (the procedure for $\epsilon + \epsilon' < \Delta + \Delta'$ is analogous). If $c_1 = c_2$, $P_{x,y} = c_1$ and $P_{x,\gamma} = c_1$, for $y - \Delta' < \gamma < y + \Delta$, i.e., it is assumed that there is a "hole" inside the class. However, if $c_1 \neq c_2$, it is necessary to determine the point (x, γ), $y - \Delta' < \gamma < y + \Delta$ where the class transition occurs, i.e., determine $p_{x,\alpha}$ such that, $P_{x,\alpha-1} = c_2$ and $P_{x_\alpha+1} = c_1$.

To determine the value α, regions centered at (x, γ), $y - \Delta' < \gamma < y + \Delta$ are sampled and, for each one, we need to calculate $\mathbf{v_{x,\gamma}}$, $d(\mathbf{v_{c_1}}, \mathbf{v_{x,\gamma}})$, $d(\mathbf{v_{c_2}}, \mathbf{v_{x,\gamma}})$ and $D_{x,\gamma} = |d(\mathbf{v_{c_1}}, \mathbf{v_{x,\gamma}}) - d(\mathbf{v_{c_2}}, \mathbf{v_{x,\gamma}})|$. γ is assigned to α when $D_{x,\gamma}$ is the smallest.

The value α was selected as described above because when $d(\mathbf{v_{c_1}}, \mathbf{v_{x,\gamma}})$ is small, it means that the mask centered at (x, γ) belongs to class c_1. The same occurs for $d(\mathbf{v_{c_2}}, \mathbf{v_{x,\gamma}})$, since $p_{x,y}$ does not belong simultaneously to two classes, if $d(\mathbf{v_{c_1}}, \mathbf{v_{x,\gamma}})$ is small, $d(\mathbf{v_{c_2}}, \mathbf{v_{x,\gamma}})$ will be large and consequently $|d(\mathbf{v_{c_1}}, \mathbf{v_{x,\gamma}}) - d(\mathbf{v_{c_2}}, \mathbf{v_{x,\gamma}})|$ will be large. However, $d(\mathbf{v_{c_1}}, \mathbf{v_{x,\gamma}})$ and $d(\mathbf{v_{c_2}}, \mathbf{v_{x,\gamma}})$ will be large for conflicting classes, i.e., the mask centered at (x, γ) belongs neither to class c_1 nor to class c_2 (transition between classes). In this case, $|d(\mathbf{v_{c_1}}, \mathbf{v_{x,\gamma}}) - d(\mathbf{v_{c_2}}, \mathbf{v_{x,\gamma}})|$ will be minimum, because a transition between the classes c_1 and c_2 was found.

Figure 2(b) shows the results obtained by the step described in Section 3.1, where pixels located in the class transitions were not classified. Figure 2(c) shows the result after applying the first iteration of the step described in this section. The pixels located in the center of the image were not classified, since it was not possible to determine which classes were closer along horizontal and vertical directions. Finally, Figure 2(d) shows the final classification, after solving the conflicting regions.

4. EXPERIMENTAL RESULTS

To evaluate the proposed methodology, experiments were performed using three texture mosaic and a synthetic mosaic generated by MRF, as shown in Figure 3. All images were classified using regions with size of 32×32 pixels, and the average rate of correct classification was 96.3%. Such results are similar to those obtained for segmentation in [3] (Figure 3(a),(b)) and, visually better (since no correct classification rate was reported) than those presented for the classification in [5] (Figure 3(b)).

Experiments varying some parameters were also performed to test the classifier robustness. The classification was carried out using different values of neighborhood order for MRF features, producing the following rates of correct classification: 91.1% for first order, 95.3% for second order, 95.1% for third order, and 92.7% for fourth order. In another experiment, the region size was varied, obtaining the following results: 94.9% for regions with 16×16 pixels, 95.1% for 32×32 pixels, and 94.5% for 64×64 pixels.

5. CONCLUSIONS AND FUTURE WORK

This work presented a texture classification method based on co-occurrence features and MRF features. Experimental results demonstrate their robustness in terms of variation in region size and number of parameters.

As future direction, we intend to experiment with a hierarchical approach for automatic determining the number of classes in the image by using MRF for calculating the probability that a region belongs to a certain class.
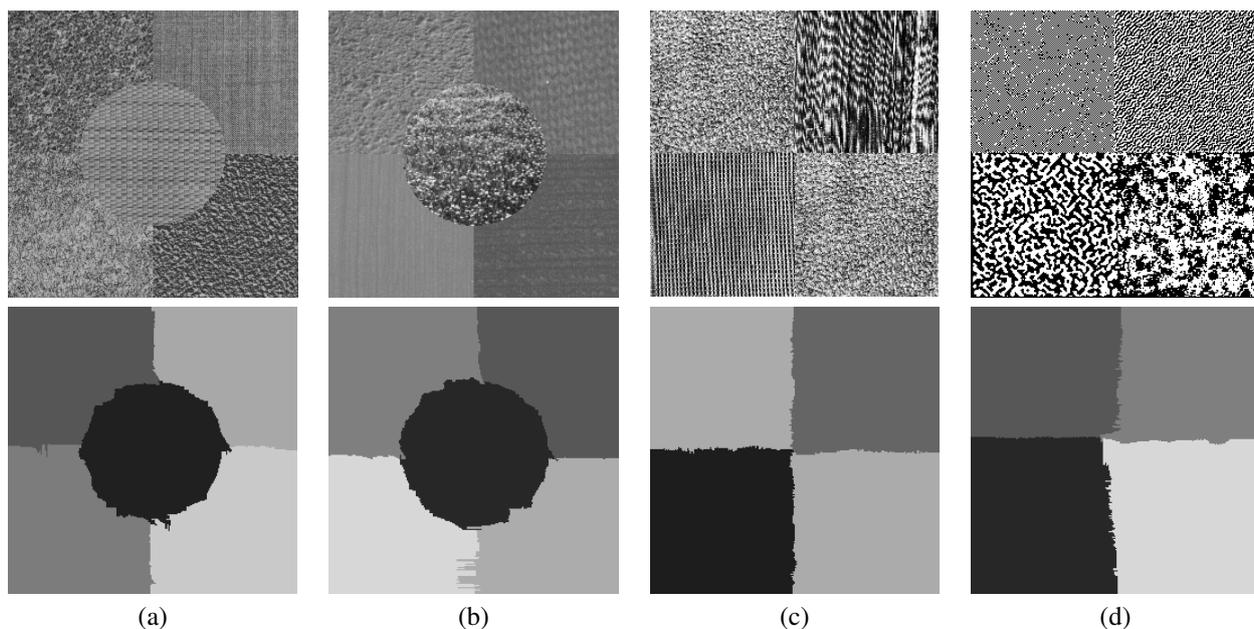
Fig. 3. Results obtained by applying our classification method. (a) texture mosaic #1 classified by means of co-occurrence features; its correct classification was 97.5%; (b) texture mosaic #2 also classified through co-occurrence features producing a correct classification of 96.6%; (c) Brodatz texture mosaic classified both through co-occurrence features and MRF features (second-order neighborhood) giving a correct classification of 94.9% and 96.5%, respectively; (d) MRF texture mosaic classified through MRF features (second-order neighborhood) producing a correct classification of 96.0%.

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