Color Textured Image Segmentation Based on Spatial Dependence Using 3D Co-occurrence Matrices and Markov Random Fields

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ABSTRACT

Image segmentation is a primary step in many computer vision tasks. Although many segmentation methods based on either color or texture have been proposed in the last decades, there have been only few approaches combining both these features. This work presents a new image segmentation method using color texture features extracted from 3D co-occurrence matrices combined with spatial dependence, this modeled by a Markov random field. The 3D co-occurrence matrices provide features which summarize statistical interaction both between pixels and different color bands, which is not usually accomplished by other segmentation methods. After a preliminary segmentation of the image into homogeneous regions, the ICM method is applied only to pixels located in the boundaries between regions, providing a fine segmentation with a reduced computational cost, since a small portion of the image is considered in the last stage. A set of synthetic and natural color images is used to show the results by applying the proposed method.

Keywords: Image segmentation; Spatial Dependence; Markov Random Fields; Color; Texture Features.

1 INTRODUCTION

The primary purpose of an image segmentation system is to extract information from the images to allow the discrimination among different objects of interest. Image segmentation is of great interest in a variety of scientific and industrial fields, with applications in medicine, microscopy, remote sensing, control of quality, retrieval of information in graphic databases, among others. The segmentation process is usually based on gray level intensity, color, shape, or texture.

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. Although several methods for unsupervised and supervised texture segmentation and classification have been proposed in the literature, there are neither formal approaches nor generic methods that are useful for a great variety of images.

The main texture feature extraction methods can be categorized into structural, statistical and spectral [Palm04]. Structural methods are based on an arrangement of textural elements. Statistical methods define textures as stochastic processes and characterize them by a number of statistical measures. Most important statistical approaches are co-occurrence matrices, autocorrelation methods, and gray level run length matrices. Spectral approaches focus on periodic pattern resulting in peaks in the frequency domain, for instance, Gabor filtering and wavelet decomposition.

The use of colors also plays an important role in the description of regions contained in an image [Lucch01]. Many techniques for feature extraction, capable of summarizing the region properties, are based on color histogram. Although such techniques are widely used in certain applications, a serious disadvantage is their incapability of incorporating spatial information into the histogram. Furthermore, histograms are susceptible to global variations in pixel intensity.

While significant advance has been achieved in texture segmentation [Tucer98] and in color image segmentation [Cheng01] separately, the combination of texture and color properties is considered as a much more challenging problem [Deng01]. However, such combination can provide more accurate information to guide the description of the image regions [Panjw95, Shafa97, Belon98, Shi95, Palm04, Chen05].

Due to the satisfactory performance in several areas, image segmentation methods based on spatial dependence have received increasing attention from sci-

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entific community [Deng04, Krish97]. Besides considering the features extracted from image regions, as usually used in region-based segmentation techniques, such methods incorporate information about a region neighborhood through the Bayesian formulation.

Among the main advantages in using segmentation based on random fields are the integration of spatial relationship between adjacent regions of the image [Dubes89], the use of several features for image description by means of the Bayesian formulation, the region labeling for generating the final segmentation obtained directly from the random field [Deng04], and the incorporation of constraints into the energy function to be minimized [Geman90].

This work describes a new image segmentation method using color texture features extracted directly from 3D co-occurrence matrices combined with spatial dependence, this modeled by a Markov random field.

The method is divided into two stages. In the first one, the centers of homogeneous regions are located by using the Dog Rabbit clustering algorithm, resulting in a coarse segmentation. The second stage is responsible for determinating the boundaries between regions, resulting in a fine segmentation. In contrast with the approach described by Fwu and Djuric [Fwu96], which employs the ICM (iterated conditional modes) in the whole image, the proposed method applies the ICM only to those pixels located in the boundaries of adjacent regions, therefore, reducing the computational cost.

The paper is organized as follows. Section 2 describes the techniques used to develop the method. In Section 3, the proposed method is presented and discussed. Experimental results obtained by applying the segmentation method are shown in Section 4. Finally, Section 5 concludes the paper with some final remarks.

2 RELATED TECHNIQUES

This section describes the techniques used to develop the proposed method, which include the Dog Rabbit clustering algorithm for locating the cluster centers in the first stage of the method, and color texture features and Markov random fields that are combined by the Bayesian formulation to allow spatial dependence during the second stage of the segmentation method.

2.1 Dog Rabbit Clustering Algorithm

The Dog Rabbit clustering method is an iterative procedure proposed by McKenzie and Alder [McKen94] and recently improved by Hill et al. [Hill05]. It uses a dynamic process to move G points to positions near the centers of clusters in the feature space.

The main idea consists of sequentially taking the sample points and moving the cluster centers toward each sample, as it is considered. The closest center is moved to the sample point under consideration, while the other ones move a lesser amount, such that only one center is more strongly attracted to each data cluster. After all iterations, each one of the G points is considered as the center of a cluster.

The displacement of the center C_j can be modeled by Equation 1, where D_j is the distance between the feature vector of the data point y_i and jth center. f_j is the *fatigue* parameter, responsible for keeping each C_j in the centroid of its corresponding cluster, and Λ is the *inhibition* parameter which allows only one center for each data cluster.

$$C_j^{'} = C_j + \alpha_j \frac{2D_{i,j}}{(1+D_{i,j})^{f_j}}(y_i - C_j) \qquad (1)$$

where

$$\alpha_j = \begin{cases} 1 & \text{if } C_j \text{ is the closest center to } y_i \\ \dfrac{D_{i,j}}{\Lambda + D_{i,j}} & \text{otherwise} \end{cases}$$

According to McKenzie and Alder [McKen94], the Dog Rabbit algorithm is more reliable than the well-known K-means clustering algorithm that is sensitive to the order in which the data are presented.

2.2 Segmentation Based on Spatial Dependence

Methods based on information regarding spatial dependence use the Bayesian formulation to relate the features of a region to its certain neighborhood [Winkl03]. In order to divide an image into homogeneous regions by grouping pixels having similar characteristics, such methods consider the existence of an observation (input image with n pixels) and a correctly, but unknown, segmented image.

Each pixel of the image is considered as a random variable that assumes values in $L = \{0, 1, \ldots, G-1\}$, where G denotes the number of regions with distinct characteristics in the image. $Y = \{y_1, y_2, \ldots, y_n\}$ denotes the set composed of the feature vectors representing the observed variables. Information about spatial dependence is modeled by a MRF (Markov random field), represented by the set of random variables $X = \{X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n\}$, where x_i belongs to the set L.

The Bayes' theorem, given in Equation 2, is used to establish the relationship between features Y and the spatial dependence of variables X, where $P(X)$ is often called the *a priori probability*. The correct segmentation for an image is that one which the labelling in set X maximizes the *a posteriori probability* $P(X|Y)$.

$$P(X|Y) = \frac{P(X)P(Y|X)}{P(Y)} \qquad (2)$$

However, the computational cost needed to determine the optimal segmentation is extremely high since it is

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not trivial to define the prior probability $P(X)$ and there are an exponential number of possible segmentations, even for images with small sizes.

Therefore, for practical purpose, segmentation techniques for approximating the optimal solution must be used. Such approximations are obtained by means of relaxation methods such as SA (simulated annealing) [Geman84], ICM (iterated conditional modes) [Besag86], MMP (maximum marginal probability) [Marro87], belief propagation [Pearl88], and graph cuts [Boyko01], which iteratively maximize probability $P(X|Y)$, after making a set of assumptions.

2.3 Color Texture Feature Extraction

In gray level images, texture can be described as an attribute representing the spatial arrangement of the pixel intensities in a region of the image. A classical approach is based on extracting several statistical measures from a gray level co-occurrence matrix, such as contrast, correlation, energy, and homogeneity [Baral95, Haral73].

The co-occurrence matrix of an image is an estimation of the second-order joint probability density of the intensity changes between pair of pixels, separated by a given distance at a certain orientation. Typically, the distance is one pixel and the orientation is quantized into four different orientations ($\theta = 0^o$, 45^o, 90^o, 135^o). Therefore, four co-occurrence matrices are generated.

Color is also a very important attribute in image analysis. Many techniques for color feature extraction are based on the color histogram. Although such techniques have been extensively used in certain applications, they have some disadvantages since spatial information is not incorporated into the histogram.

Since the segmentation method proposed in this work uses color textured images, an extension of the traditional gray level co-occurrence matrices is required to extract proper features. The approach proposed by Dacheng et al. [Dache02] is used to describe texture features in color images. Initially, the RGB color model is converted into HSI model, since it separates the intensity and color components. Then, H, S and I components are quantized into 8, 4 and 4 bins, respectively. Nine orientations are used to define the neighborhood of a pixel along the H, S and I planes, as shown in Figure 1.

From these 3D co-occurrence matrices, four textural features are calculated (angular second moment, contrast, correlation, and entropy), producing a total of 36 measures, since nine matrices are calculated.

2.4 Markov Random Field

In order to define the image pixel interaction, an image is considered as a stochastic process, that is, $X = (X_1 = x_1, X_2 = x_2, ..., X_n = x_n)$, where x_i belongs to set

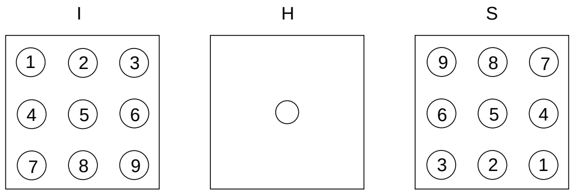

Figure 1. Orientations used to define the neighborhood of a pixel using the HSI model. Equal labels indicate the considered variations of intensity, crossing the central pixel in H plane.

L, defined in the beginning of Section 2.2. A realization of the image is vector $x = (x_1, x_2, \ldots, x_n)$. Thus, the sample space has $\{0, 1, \ldots, G-1\}^n$ different realizations.

Through the stochastic modeling, an image can be considered as a set of random variables. Thus, it is possible to determine the joint distribution of such variables, denoted $P(X)$. However, due to the lack of information regarding the dependence of the random variables and the exponential number of parameters that have to be estimated, Abend et al. [Abend65] concluded that only the local interactions between neighbors can be considered. As a consequence, only approximated solutions for the optimum segmentation may be obtained in acceptable computational time.

Some stochastic models based on local dependence have been proposed, such as Markov Mesh, Pickard model, and Markov random field. All these models estimate the joint probability $P(X)$ by means of Equation 3, where Z is called partition function and $H(X)$ represents an energy function which depends only on local interactions among the random variables [Winkl03].

$$P(X) = \frac{1}{Z} \exp(-H(X)) \tag{3}$$

3 PROPOSED METHOD

The aim of the proposed method is to segment a color textured image in G regions having similar features. The method is composed of two stages. The first stage segments the homogeneous regions of the image by using the Dog Rabbit clustering method and a bidimensional histogram, resulting in a coarse segmentation. In the second stage, considering that the features follow the Gaussian probability distribution, the ICM is used to determine the location of boundaries between adjacent regions.

The diagram in Figure 2 illustrates the steps of each stage. Since the ICM is applied only to pixels located in boundary regions, this approach significantly reduces the computational costs.

During the first stage, the input image is converted from RGB into HSI color model. The image is divided into a number of square windows, being allowed the overlapping of distinct regions. For each window, 3D

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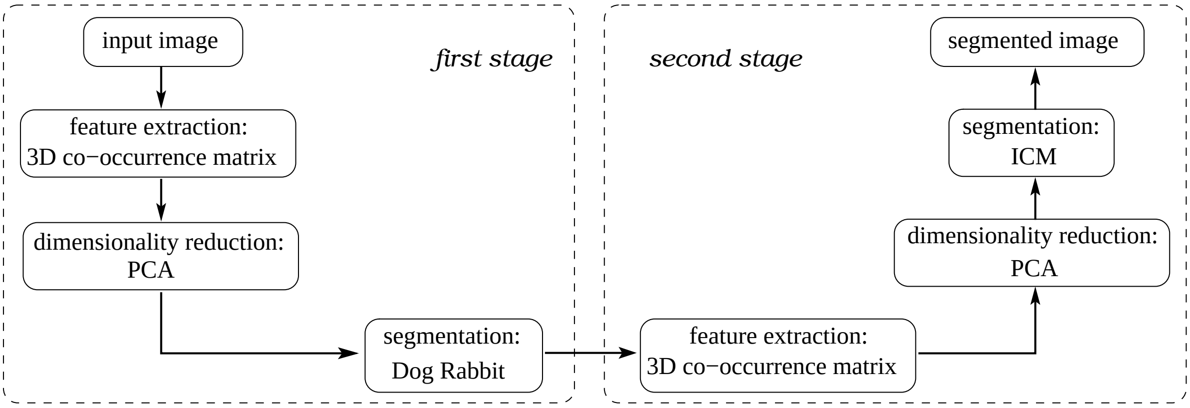

Figure 2. Diagram illustrating the two stages of the proposed segmentation method.

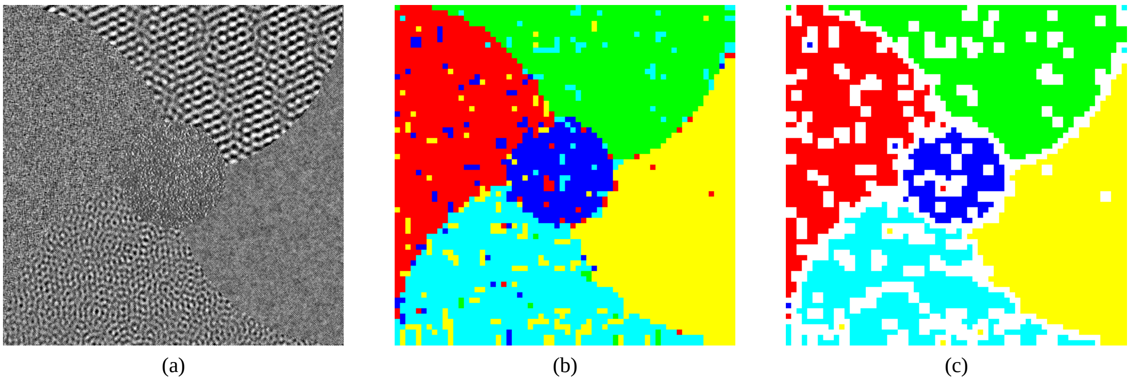

Figure 3. Example of coarse segmentations. (a) texture mosaic; (b) resulting segmentation by applying only a clustering algorithm; (c) segmentation obtained with the bidimensional histogram.

co-occurrence matrices are calculated to generate 36 statistical measures. Such measures compose a feature vector, which is used to describe the region of the image contained in the sampled window.

Additionally, principal component analysis (PCA) is applied to each feature vector to reduce the data dimensionality. Afterwards, all measures obtained from the co-occurrence matrices are rescaled to have unit variance and zero mean. The Dog Rabbit clustering method is applied in the feature vectors aiming at locating the G cluster centers which divide the image in homogeneous classes. Finally, each sampled window is labeled with a value in set L.

Once the initial clustering is concluded, a bidimensional histogram is calculated. In this histogram, the entry (x,y) contains the occurrence frequency of each G possible labels. A pixel located at (x,y) is assigned to the class i if the entry (x,y) has only non zero values in i; otherwise, that pixel will be considered in the second stage of the algorithm. Therefore, the more overlapping windows, the more precise the result of the first stage will be.

Figure 3 shows an instance of a coarse segmentation that may be obtained by computing the bidimensional histogram and setting as segmented only those regions belonging to a single class. As a result, the parameter estimation required by the second stage is performed without considering regions located in the boundaries between two classes (white regions in Figure 3(c)). Therefore, the parameters are estimated within samples in a single class, as desired.

To segment those pixels not labeled in the first stage, the ICM method is applied to estimate an labeling which maximizes the probability *a posteriori*, shown in Equation 2. Since the ICM maximizes only the local probability of a random variable, given by Equation 4, its computational cost is lower than the costs presented by other methods. The Equation 4 shows the terms which need to be maximized, where η_i represents a local neighborhood of random variable.

$$x_i \leftarrow \arg\max_{v \in L} \{P(X_i = v|\eta_i) \\ P(Y_i = y_i|X_i = v)\} \quad (4)$$

Assuming that the features extracted to each pixel follow a Gaussian distribution, Jackson and Landgrebe [Jacks02] approximated Equation 4 by 5. In such approximation, μ_v and Σ_v denote, respectively, the mean vector and the covariance matrix of the vth class in the image; m represents the number of neighbors for x_i that belong to regions different from v; finally, β is a constant weight coefficient which defines how strong is

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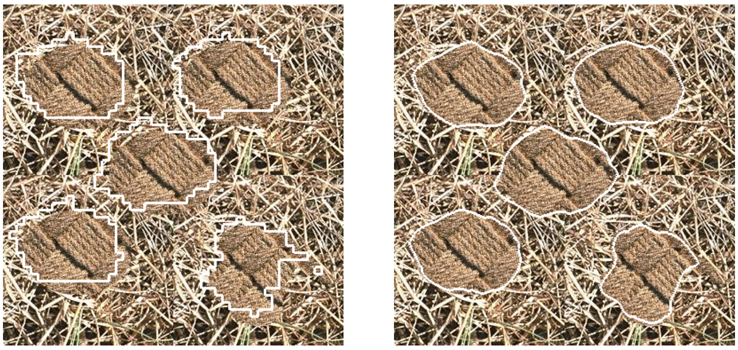

(a) (b)

Figure 4. Segmentation of a texture mosaic image. (a) after the Dog Rabbit clustering (first stage); (b) after 25 cycles of ICM using β=0.8 (second stage).

the interaction among adjacent pixel within a neighborhood [Winkl03].

$$x_i \leftarrow \arg\min_{v \in L} \left\{ \ln|\Sigma_v| + 2m\beta + (y_i - \mu_v)^{\mathrm{T}} \Sigma_v^{-1} (y_i - \mu_v) \right\} \quad (5)$$

Although the feature extraction and dimensionality reduction are performed in the same manner as that in the first stage, the windows are sampled differently, centered in each unsegmented pixel. Therefore, each vector y_i contains the result of PCA executed over features extracted from 3D co-occurrence matrices obtained from a window centered in ith pixel.

Once the feature vector computation is concluded, it is enough to execute a few cycles of ICM to label those pixels that remain unlabeled after the first stage. Finally, after the union of results obtained in both stages, the image is completely segmented.

4 EXPERIMENTAL RESULTS

A set of synthetic and natural color images is used to illustrate the results by applying the proposed method. Figure 4 shows the segmentation of a color mosaic image, using only the Dog Rabbit clustering algorithm (first stage of the proposed method) and after the second stage, respectively.

It can be observed that the last stage provides an improved segmentation due to the local adaptation of the ICM algorithm. The boundaries between the regions are smoother and better identified.

To evaluate our methodology, experiments were performed by using three texture mosaics and real images, shown in Figure 6. Each image was partitioned into windows with size of 24×24 pixels for feature extraction in both stages.

Since the ICM is used during the second stage of the method, the final segmentation presents a fine adaptation to the boundaries between adjacent regions, such as the result shown in Figure 5.

Although the ICM algorithm is used in the second stage of our method, when compared to methods that

Figure 5. Segmentation with a fine adaptation to the boundaries between regions.

apply ICM in the entire image, the computational cost is lower since only the pixels located in the region boundaries are considered in the second stage.

The number of segmented pixels and corresponding percentage during the two stages are shown in Table 1. The percentage depends on the amount of boundary regions present in the image.

Image	number of segmented pixels first stage	second stage
Figure 4(b)	129,920 (88.11%)	17,536 (11.89%)
Figure 6(a)	118,848 (80.60%)	28,608 (19.40%)
Figure 6(b)	189,744 (72.38%)	72,400 (27.62%)
Figure 6(c)	243,520 (92.90%)	18,624 (7.10%)
Figure 6(d)	228,352 (87.11%)	33,792 (12.89%)

Table 1. Number of segmented pixels during the first (Dog Rabbit) and second stage (ICM) of the proposed method.

5 CONCLUSIONS

This work presented a new image segmentation method using color texture features extracted from 3D co-

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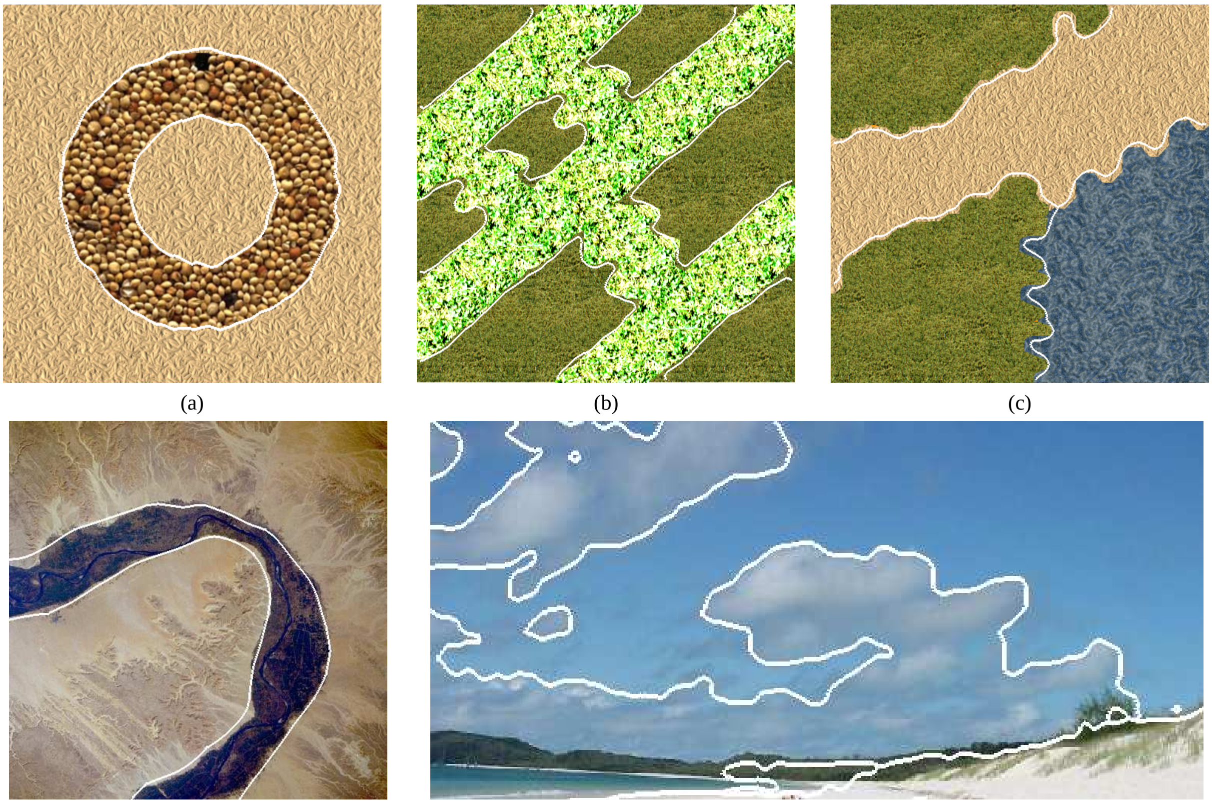

Figure 6. Results obtained by our segmentation method after 50 cycles of ICM, with β=0.8 and windows composed of 24$\times$24 pixels for feature extraction. (a)-(b) texture mosaics with 384$\times$384 pixels; (c) texture mosaic with 512$\times$512 pixels; (d) satellite image composed of 512$\times$512 pixels; (e) natural image with 512$\times$256 pixels.

occurrence matrices combined with spatial dependence modeled by a Markov random field.

The application of ICM only to pixels located in the boundaries of regions reduced the computational cost, also providing an improved segmentation due to its local adaptation.

The effectiveness of the proposed method was demonstrated by several experiments using synthetic and real color images. An extension of the method for segmenting color-texture regions in video data is planned as future work.

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