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

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# Organization

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# 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.
- ↪ Texture can be characterized by local variations of pixel values that repeat in a regular or random pattern on the object or image.
- ↪ The main texture feature extraction methods can be categorized into structural, statistical and spectral.

# Introduction

- ↪ 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.

# Introduction

↪ The use of colors also plays an important role in the description of regions contained in an image.

↪ Many techniques forfeature 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.

# Dog Rabbit Clustering Algorithm

- ↪ The Dog Rabbit clustering method is an iterative procedure proposed by McKenzie and Alder and recently improved by Hill et al.
- ↪ 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.

# Dog Rabbit Clustering Algorithm

$$\mathbf{C}_j^{'} = \mathbf{C}_j + \alpha_j \frac{2D_{i,j}}{(1 + D_{i,j})^{f_j}} (\mathbf{y}_i - \mathbf{C}_j)$$

where

$$\alpha_j = \begin{cases} 1 & \text{if } \mathbf{C}_j \text{ is the closest center to } \mathbf{y}_i \\ \dfrac{D_{i,j}}{\Lambda + D_{i,j}} & \text{otherwise} \end{cases}$$

# Segmentation Based on Spatial Dependence

↪ 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. $Y = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_n\}$ 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 $L$.

# Segmentation Based on Spatial Dependence

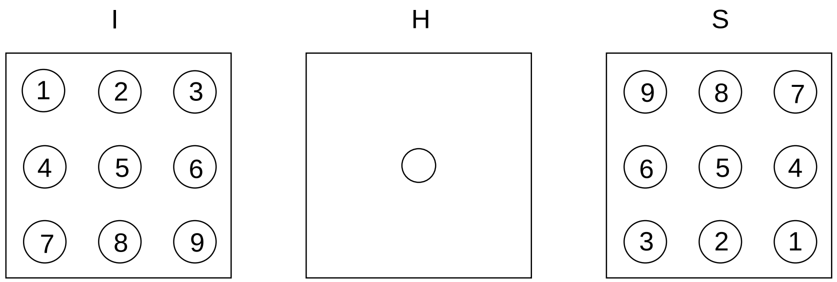
$\hookrightarrow$ The Bayes' theorem, given in Equation , is used to establish the relationship between features Y and the spatial dependence of variables X, where $\mathrm{P}(\mathrm{X})$ is often called the *a priori probability*. The correct segmentation for an image is that one which the labelling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

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

# 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.
- ↪ 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.

# Color Texture Feature Extraction




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.

# Markov Random Field

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

# Markov Random Field

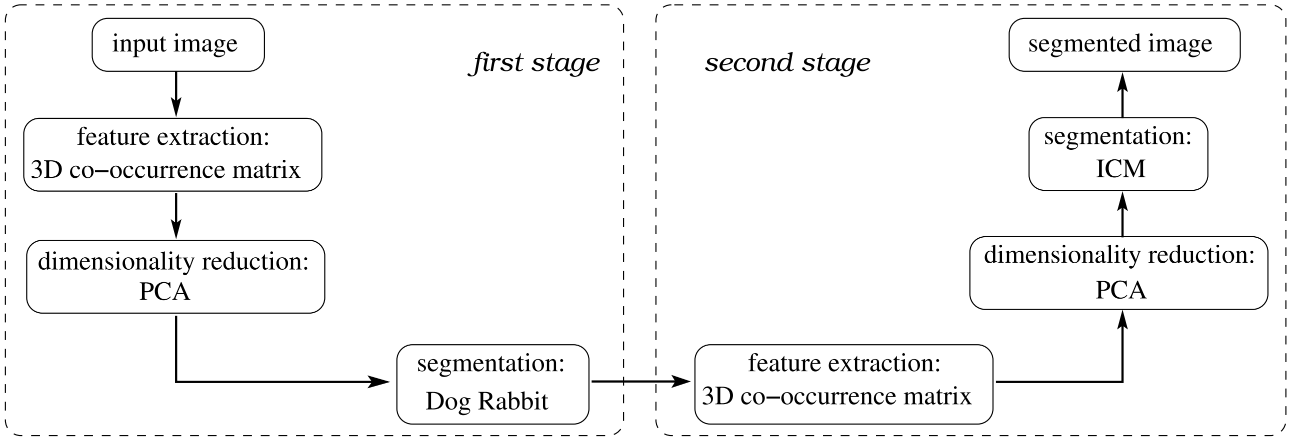
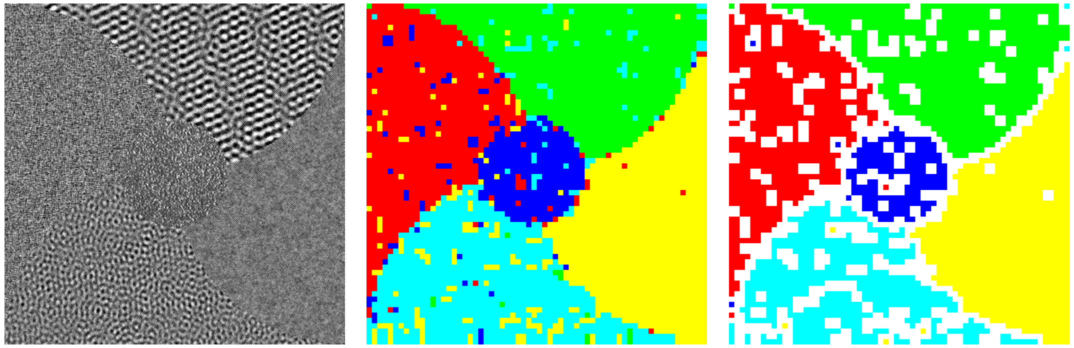



Diagram illustrating the two stages of the proposed segmentation method.

# Markov Random Field



# Proposed Method

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

# Proposed Method

Segmentation with a fine adaptation to the boundaries between regions.

## Proposed Method

- ↪ 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. For each window, 3D co-occurrence matrices are calculated to generate $36$ statistical measures.
- ↪ 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 $\mathrm{L}$.

## Proposed Method

$\hookrightarrow$ 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.

# Experimental Results

- ↪ A set of synthetic and natural color images is used to illustrate the results by applying the proposed method.
- ↪ 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.

# Experimental Results

Segmentation with a fine adaptation to the boundaries between regions.

## Experimental Results

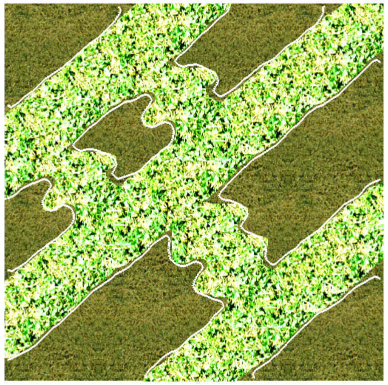
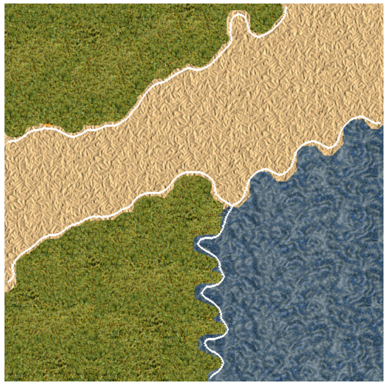
- Although the ICM algorithm is used in the second stage of our method, when compared to methods that apply ICM in the entire image, the computational cost is lower since only the pixels located in the region boundaries are considered in the second stage.
- The number of segmented pixels and corresponding percentage during the two stages are shown in the following table. The percentage depends on the amount of boundary regions present in the image.

# Experimental Results

| Image | number of segmented pixels first stage | second stage |
|---|---|---|
| 1 | 129,920 (88.11%) | 17,536 (11.89%) |
| 2 | 118,848 (80.60%) | 28,608 (19.40%) |
| 3 | 189,744 (72.38%) | 72,400 (27.62%) |
| 4 | 243,520 (92.90%) | 18,624 (7.10%) |
| 5 | 228,352 (87.11%) | 33,792 (12.89%) |

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

# Experimental Results

# Conclusions

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