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A Neural Approach for Color-Textured Images Segmentation

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Abstract—In this paper, we present a neural approach for unsupervised natural color-texture image segmentation, which is based on both Kohonen maps and mathematical morphology, using a combination of the texture and the image color information of the image, namely, the fractal features based on fractal dimension are selected to present the information texture, and the color features presented in RGB color space. These features are then used to train the network Kohonen, which will be represented by the underlying probability density function, the segmentation of this map is made by morphological watershed transformation. The performance of our color-texture segmentation approach is compared first, to color-based methods or texture-based methods only, and then to k-means method.

Keywords—Segmentation, color-texture, neural networks, fractal, watershed.

I. Introduction

SEGMENTATION is a fundamental and important step for any attempt to interpret or analyze an image automatically. This technique aims to divide an image into homogeneous regions according to certain criteria (intensity, color, texture), it is the core of any application involving the recognition and detection of objects in images. The application of the segmentation generally involves two steps, the first one is to extract the features for each pixel in the image, and the second is to use these features to determine the uniform regions in the image.

In this paper, we present an unsupervised segmentation approach combining the texture and color features, the first step is to extract from each pixel a local fractal features vector using the differential box counting method. In order to have the vector that characterizes the color-texture information, the fractal feature vectors are concatenated with the color vectors represented in the RGB color space.

After calculating the color-texture features, we first place the feature vector of each pixel into the feature space which forms a cloud of observations and we make a projection of these on a self-organizing map. To help extract the homogeneous regions in this map, we present in the first stage the information in each cell of this map by the probability density function value (PDF) estimated by a nonparametric procedure, in the second stage we extract automatically the modal regions using watershed transformation. The classification stage is to take the weight vectors corresponding to the modal regions detected as prototypes of homogeneous regions in the image. Weights from each of these prototypes are the basis of the assignment of any pixel of the image to one of the classes extracted.

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In the last section, we present a comparison of results obtained using only the texture or color with the results obtained by the combination color-texture, finally we test the efficiency of our segmentation approach with the k-means method.

II. Feature Extraction

In order to plot the pertinent attributes that characterize better the objects, each classification process starts with an acquisition step of observation. In this study, we use a combination of texture and color features, first, we extract the texture information from each pixel using Fractal Dimension calculated by the differential box counting method, and then we combine this Fractal features with the color features represented on RGB color space.

A. Fractal Features

In the 70s, fractal geometry saw the light of existence offering us new concepts so that we can finally understand some complex phenomena that we haven't been able to comprehend, fractal concept application fields are numerous, including image analysis.

When it comes to image analysis application, fractal geometry is mostly used throughout the concept of fractal dimension (FD), however in this study we have chosen to work with the differential box counting method [1], [2], as it can be computed and applied to patterns with or without self-similarity.

The stages used by the differential box counting method mentioned above begin by partitioning the image space into boxes of different sizes r, secondly the probability N(r) is calculated as the difference between the maximum and minimum gray levels for each one of the boxes, afterwards the fractal dimension is estimated using the following equation:

$$FD = \lim_{r \to 0} \frac{ln[N(r)]}{ln(\frac{1}{r})} \tag{1}$$

To compute the fractal dimension of a pixel $I(i,j)$ for image I, we use the local $m \times m$ pixel window $W(i,j)$:

1) For various $r \in [0,1]$.
   - Divide $W_{(i,j)}$ into $(1/r)^2$ boxes.
   - Divide the range of intensities [0..255] into $1/r$ levels numbered $1..1/r$.
   - For each box $b(p,q) \in W_{(i,j)}$ do:
     a) $l \leftarrow minimum(\, b(p,q)\,)$
     b) $k \leftarrow maximum(\, b(p,q)\,)$
     c) $n_{p,q}(r) \leftarrow l - k + 1$

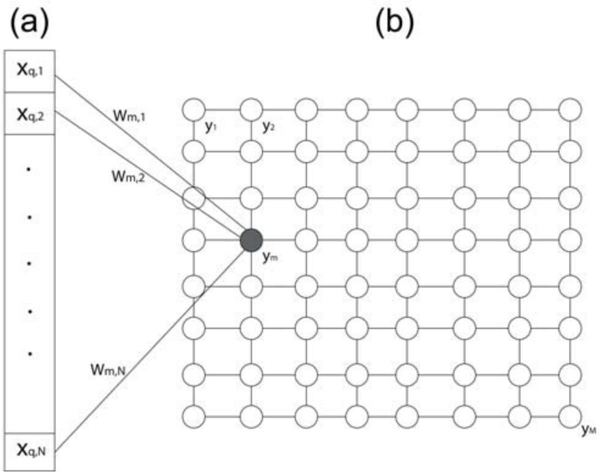

Fig. 1 Kohonen map layers: (a) Input Layer, (b) Output Layer

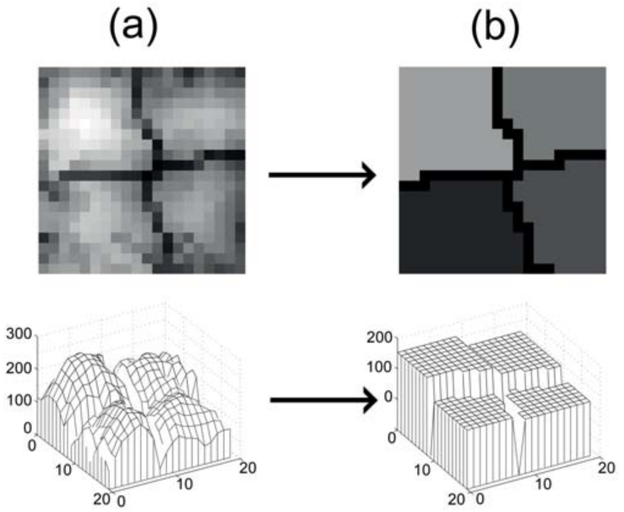

Fig. 2 (a) PDF (b) PDF modal regions

- $N(r) = \sum_{p,q} n_{p,q}(r)$

2) Do line-fit of $N(r)$ and $ln(1/r)$.
3) The Fractal Dimension FD is obtained by linear regression of this line-fit.

In this paper, we use the differential box counting method as a manner to extract different features from the textural image. We have used not only the original image (I_1) but also derived images:

- High gray valued image (I_2):

$$I_2(i,j) = \begin{cases} I_1(i,j) - L_1, & if \quad I_1(i,j) > L_1 \\ 0, & otherwise \end{cases} \tag{2}$$

- Low gray valued Image (I_3):

$$I_3(i,j) = \begin{cases} 255 - L_2, & if \quad I_1(i,j) > (255 - L_2) \\ I_1(i,j), & otherwise \end{cases} \tag{3}$$

- Horizontally smoothed image (I_4):

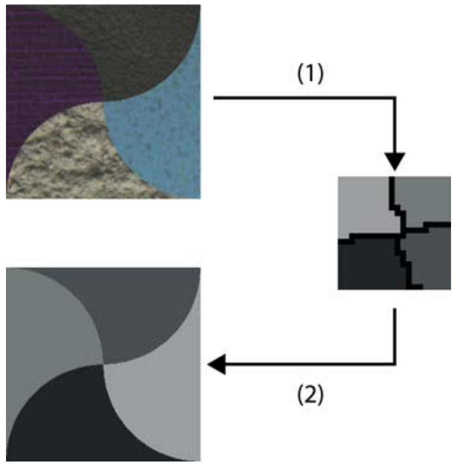

Fig. 3 Image segmentation principle: (1) Detecting the modal regions from the image (2) Assigning to each pixel the closest modal region value

$$I_4(i,j) = \frac{1}{2w+1} \sum_{k=-w}^{w} I_1(i, j+k) \tag{4}$$

- Vertically smoothed image (I_5):

$$I_5(i,j) = \frac{1}{2w+1} \sum_{k=-w}^{w} I_1(i+k, j) \tag{5}$$

Finally, we have for each pixel $I(i,j)$ a vector $X_q = \{f_1, f_2, f_3, f_4, f_5\}$ where f_k is the fractal dimension of the sliding window $W_{k(i,j)}$ from I_k.

B. Color Features

With fractal extraction method, only the luminance attribute was considered, so to add color information to our descriptors, we concatenates the fractal vectors with the color RGB vectors of each pixel.

III. Segmentation of Color-Texture Image Using the Kohonen Map

The unsupervised classification methods are very powerful tools for the automatic detection of relevant subgroups in a data set, one of these methods is self-adaptive map proposed by Kohonen [3]. In our work, we use this method to classify our cloud of observation composed from the texture and color extracted features.

A. Kohonen Map Learning Phase

Let $\Gamma = \{X_1, X_2, X_3, ..., X_Q\}$ be a sample of Q observations in a N-dimensional space such as $X_q = [x_{q,1}, x_{q,2}, ..., x_{q,N}]^T$, $q = 1, 2, ..., Q$. The Kohonen network is made of two layers, the first one is the input layer which is composed of N attributes of the observation X_q. The output layer is composed of M neural units regularly distributed on the map which elaborates prototypes of the data.

The neural units of the first layer are connected to the units of the second layer Fig. 1. Each interconnection from an input

TABLE I
IMAGE 1 SEGMENTATION RESULTS

Features	Kohonen segmentation rate	K-means segmentation rate
RGB	0.57%	0.61%
Fractal	3.59%	4.01%
Fractal and RGB	0.44%	0.51%

TABLE II
IMAGE 2 SEGMENTATION RESULTS

Features	Kohonen segmentation rate	K-means segmentation rate
RGB	38.55%	37.64%
Fractal	5.96%	5.92%
Fractal and RGB	3.93%	4.02%

unit j to an output unit m has a weight $W_{m,j}$. That means that each output unit m has a corresponding weight vector $W_m = [W_{m,1}, W_{m,2}, \dots \dots, W_{m,N}]^T$.

The followed steps of the learning algorithm are:

1) Initializing the weights of the neurons in the Kohonen layer by giving them small random values.
2) Presenting an input vector X_q.
3) Finding the winning node m^* using the Euclidean distance between the vector X_q and the nodes of the output layer.
4) Updating the weights W_i winner node, as well as those around him, using the equation 17.
5) Decreasing the size of the neighborhood area winners nodes.
6) Decreasing the learning coefficient (t) .
7) Going back to Step 2. , or else complete learning.

$$\begin{cases} W_m(t) = W_m(t-1) + \alpha(t).[X_q - W_m(t-1)] \\ \qquad if\ m\ is\ the\ winning\ node. \\ W_m(t) = W_m(t-1) + \alpha(t).h_m(t).[X_q - W_m(t-1)] \\ \qquad if\ m \in V(m^*, r(t)). \end{cases} \tag{6}$$

where:

- $\alpha(t)$ is the learning coefficient at the time.
- $r(t)$ is the interaction radius which depends on the number t of the iteration.
- $V(m, r)$ is the neighborhood of a neural unit m with a radius r, defined by :

$$V(m,r) = \{m' \in [0, M[\ ,\ m' \neq m \mid d(U_m, U_{m'}) \leq r\} \tag{7}$$

- $d(U_m, U_{m'})$ is the Euclidean distance between the position vector U_m and U'_m of the m and m neural units.
- $h_m(t)$ is the interaction function which depends on the proximity radius $r(t)$ defined by:

$$h_m(t) = exp(-\frac{d(U_m, U_{m'})^2}{2r(t)^2}) \tag{8}$$

B. Visualization of the PDF on the Kohonen Map

Once the learning phase is processed, the determined weight vectors in the multidimensional data space are used to estimate the underlying probability density function (PDF). For this purpose, we use the nonparametric Parzen estimate[4] defined by:

$$p(W_m) = \frac{1}{Q} . \sum_{q=1}^{Q} \frac{1}{V[D(W_m)]} \Omega(\frac{W_m - X_q}{h_Q}) \tag{9}$$

where:

- $\Omega(x) = \frac{1}{\sqrt{2\pi}} exp(\frac{-1}{2} X^T.X)$.
- $D(W_m)$ is the domain estimation. When it corresponds to an sphere with h_Q radius centered in W_m.
- $V[D(W_m)] = \frac{\pi^{\frac{1}{2}}}{\Gamma(\frac{N}{2}+1)} h_Q^N$ with $\Gamma(\frac{N}{2}+1) = \frac{(N+1)!\sqrt{\pi}}{2^{(N+1)(\frac{N+1}{2})!}}$ and $h_Q = h_0.\sqrt{Q}$

C. Modal Regions Extraction

To detect modal regions of the PDF, as a first step, we apply a numerical morphological opening on this estimation, after that, we use our watershed technique [5], [6] to extract modal regions of the PDF Fig. 2.

D. Segmentation

After extracting the modal regions on the map, we assign to each pixel of the image, which is represented by its vector of textural features, the closest modal region of this pixel Fig. 3.

IV. RESULTS

In order to assess our segmentation approach, we have tested it on two images composed of several color textures from Outex texture database[7]. The first image is formed of three different textures, while the second image is composed of four different textures.

After the extraction phase, we have segmented them by using our unsupervised segmentation approach. To evaluate correctly the segmentation results, we have compared them with ground truth images. Fig. 4 show the visual comparison between the results obtained by the use of the color and the texture features separately, and the results obtained by the combination of this features.

The following tables represent the segmentation results obtained for two images, the segmentation rate is calculated using our segmentation approach and k-means method.

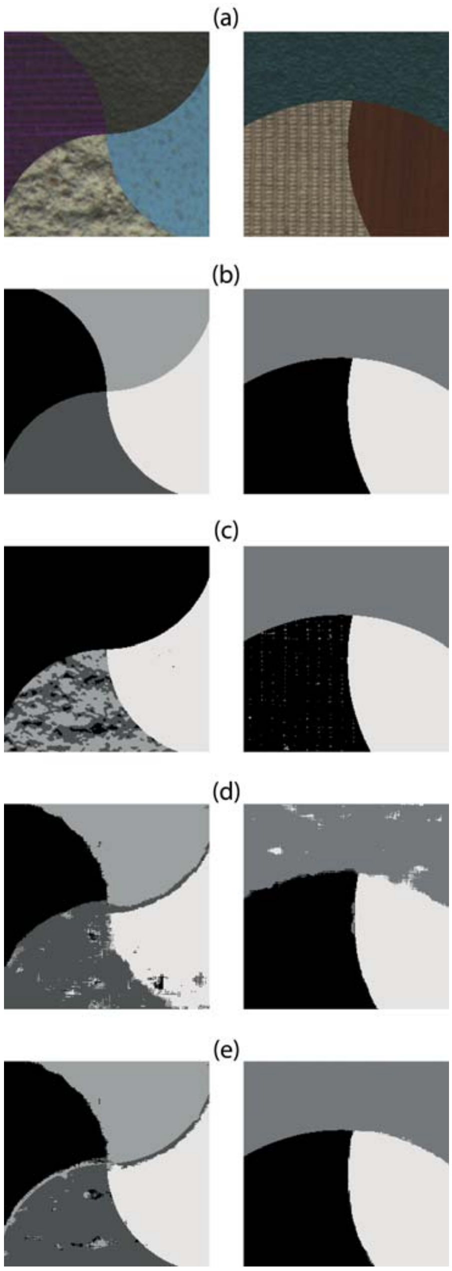

Fig. 4 (a) Color texture images (b) Ground truth (c) Color segmentation results (d) Fractal segmentation results (e) Color-fractal segmentation results

V. Conclusion

In this paper, we present a new color-textural image segmentation approach, based on the combination of Kohonen map and morphological watershed transformations, by using a combination of fractal texture features and RGB color information.

The results shows that adding color information to fractal descriptors increases the precision of the segmentation, and after comparing it with the k-means method results, it has been asserted that the segmentation rate obtained by our segmentation approach is very promising.

As perspective, we search to enhance our segmentation approach by using other texture features combined with other color spaces information. Besides, we search to extend our approach to 3D image segmentation.

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