COLOR AND TEXTURE BASED SEGMENTATION ALGORITHM FOR MULTICOLOR TEXTURED IMAGES

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Abstract: We propose a color-texture image segmentation algorithm based on multistep region growing. This algorithm is able to deal with multicolored textures. Each of the colors in the texture to be segmented is considered as reference color. In this algorithm color and texture information are extracted from the image by the construction of color distances images, one for each reference color, and a texture energy image. The color distance images are formed by calculating *CIEDE2000* distance in the $L^*a^*b^*$ color space to the colors that compound the multicolored texture. The texture energy image is extracted from some statistical moments. The method segment the color information by means of an adaptative *N*-dimensional region growing where *N* is the number of reference colors. The tolerance parameter is increased iteratively until an optimum is found and its growth is determined by a step size which depends on the variance on each distance image for the actual grown region. The criterium to decide which is the optimum value of the tolerance parameter depends on the contrast along the edge of the region grown, choosing the one which provides the region with the highest mean contrast in relation to the background. Additionally, this color multistep region growing is texture-controlled, in the sense that an extra condition to include a particular pixel in a region is demanded: the pixel needs to have the same texture as the rest of the pixels within the region. Results prove that the proposed method works very well with general purpose images and significantly improves the results obtained with other previously published algorithm (Fondón et al, 2006).

1 INTRODUCTION

In the literature there are many different region-growing algorithms. Most of them applied to grey-scale images and some of them extended to color images. Hojjatoleslami and Kittler (Hojjatoleslami and Kittler, 1998) presented a region-growing method based on two different contrast measures but it has a poor efficiency. Adams and Bischof (Adams and Bishop, 1994) proposed a method for grey-scale images, where the seeds are selected manually. The method depends on the order in which the pixels are analyzed. Fan et al.(Fan et. al., 2001) extended the previously mentioned technique to color images. Then, they improved the algorithm selecting automatically the seeds and proposed a new method for pixel labeling (Fan et. al., 2005). Cheng (Cheng, 2003) published a region-growing approach to color segmentation using 3D clustering and relaxation labeling. The three last methods mentioned take only into account the color information but not the texture one and for many natural scenes it is very important to consider both. Finally, Maeda et al. (Maeda et al., 1999) have proposed a region-growing algorithm that joins color and texture information by applying fuzzy sets, performing a region-growing procedure based on a fixed homogeneity parameter. This method is not adaptative. There are some adaptive region-growing algorithms (Hao et. al, 2000), (Pohle and Toennies, 2001), but they are specifically designed to work with a particular kind of image and are computationally inefficient. In a previous work an adaptive and efficient algorithm for general-purpose color and textured images segmentation was proposed by the authors (Fondón et al, 2006). Nevertheless, when multicolored textures are present in the image, the results are not completely satisfactory. In this paper we propose a new method that solves this problem.

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2 ALGORITHM DESCRIPTION

2.1 Reference Colors and Texture

The algorithm will segment all pixels in the image with color and texture similar to the ones present in an area selected by the user.

2.2 Color Information

2.2.1 $L^*a^*b^*$ Color Space

A perceptually uniform color space is needed so that distances between colors measured in this space are correlated with color differences according to human perception. We have chosen the $L^*a^*b^*$ color space that is a perceptually uniform orthogonal Cartesian coordinate system (Plataniotis and Venetsanopoulos, 2000).

2.2.2 Anisotropic Diffusion

Anisotropic diffusion is used for the denoising step. This is a non linear filtering method stronger in the homogeneous parts of the image and weaker in the edges (Perona and Malik, 1990).

2.2.3 Reference Colors

In order to find the reference colors, we perform a clustering operation with the well-known *k-means* algorithm in the $L^*a^*b^*$ color space. To obtain the value k of numbers of clusters automatically, we use Dunn's coefficient (Maulik and Bandyopadhyay, 2002)

$$D = \min_{1 \le i \le k} \left\{ \min_{1 \le j \le k, j \ne i} \left\{ \frac{d(c_i, c_j)}{\max\limits_{1 \le n \le k} \left(d'(c_n) \right)} \right\} \right\} \quad (1)$$

where $d(c_i,c_j)$ is the Euclidean distance between cluster i and cluster j, that is, the inter-cluster distance. $d'(c_n)$ is the intra-cluster distance for We assume that, in multicolored textures, the number of different colors is less or equal to 16. So, we perform 16 clusterings beginning from k=1 to k=16. We select the value of k that provides the highest value of D, which leads to a maximum inter-cluster distance and a minimum intra-cluster distance. Then, the k reference colors are defined as the centroids of the k clusters in $L^*a^*b^*$ color space. In Figure 1 we can see an example.

2.2.4 Distance Images

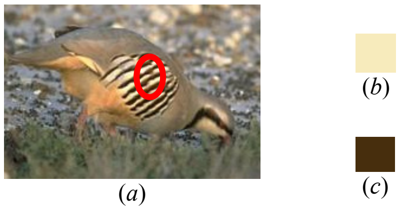


Figure 1: From the original image (a) the user selects a region, circled in red, where a multicolored texture is present. The reference colors obtained with k-means algorithm and Dunn coefficient are shown in images (b) and (c).

Once the reference colors are obtained, the distances between every single pixel of the image and each of the reference colors are calculated. We have chosen CIEDE2000 as the distance metric. This measure has been extensively tested and outperformed other existing color difference formulae (Luo et. al., 2001). Then, a new set of images is built, where each pixel value will be the CIEDE2000 color difference to each of the reference colors. In order to obtain a better visualization, we invert this image, that is, those pixels whose values are similar to the reference ones, will appear light in a dark background. These inverted images are called the *distance images* In Figure. 2, there is an example for the reference colors shown in Figure. 1.

2.3 Texture Information

The proposed method extracts texture features only from the luminance component (L^*) of the original image and not from the chrominance ones (a^*, b^*). This assumption is based on previous works: the psychophysical studies of Poirson and Wandell suggest that color and pattern information in the human visual system are processed separately (Poirson and Wandell,1996). Mojsilovic et al.(Mojsilovic et al, 2000), state that human perception of pattern is unrelated to the color content of an image. Mäenpää and Pietikäinen (Mäenpää and Pietikäinen, 2004) conclude that it seems that texture information should be extracted from the luminance component, whereas color is more a regional property. The texture features employed in this method are based on some local low statistical moments (Tuceryan., 1994) In order to justify the choice of first order statistics for texture feature extraction, Zamperoni et al. (Zamperoni et al,1995) state that although one can construct some patterns for which the choice of first order statistics does not work, the converse is true for a surprisingly high number of real images representing natural scenes of a given type, as confirmed by the experiments reported in Lowitz (Lowitz, 1983) and in Kim (Kim, 1986).

The algorithm calculates for every pixel, four statistical moments m_{pq} with $p,q=\{0,1\}$ by processing the L^* component with local masks expressed in a normalized coordinate system. A formal expression of these moments is shown in equation (2).

$$m_{pq} = \frac{1}{W^2} \sum_{m=i-W/2}^{i+W/2} \sum_{n=j-W/2}^{j+W/2} f(m,n) x_m^p y_n^q;$$
$$x_m = \frac{m-i}{W/2};\ y_n = \frac{n-j}{W/2}; \qquad (2)$$
$$i,j \in image,\ p,q = 0,1$$

W is the window width, (i,j) are the pixel coordinates for which the moments are computed, (m,n) the coordinates of another pixel which falls within the window, $(x_m\ y_n)$ are the normalized coordinates for (m,n), and $f(m,n)$ is the value of the L^* component at the pixel with coordinates (m,n). This normalized expression leads us to compare among pixel moments and it is equivalent to the finite convolution of the image with a mask. The sizes of these masks have been fixed to the size of the selection box. Usually, for each segmentation this size will be different, so the algorithm will be automatically adapted to the texture we want to isolate. With all these parameters, we can build four new images M_{pq} with $p,q=\{0,1\}$ corresponding to each statistical parameter. To this purpose we assign to each pixel a value equal to the previously calculated moment m_{pq}. Afterwards, we defined new images calculated from the energy of the moments. We called them *energy images E00*, *E01*, *E10* and *E11* and they represent the strength of each moment around the pixel location. The computation of the energies follows equation (3).

$$E_{pq}(i,j) = \frac{1}{W^2} \sum_{m=i-W/2}^{i+W/2} \sum_{n=j-W/2}^{j+W/2} M_{pq}^{\ 2}(m,n). \qquad (3)$$

$E_{pq}(i,j)$ is the energy corresponding to the pixel with coordinates (i,j) in the image M_{pq}, W is the window width, $M_{pq}(m,n)$ is the value of the pixel with coordinates (m,n) in the moment image M_{pq} and $p,q=\{0,1\}$Each pixel is now characterized with four values, one from each energy image. They are considered as coordinates in a four-dimensional space. Subsequently, in order to assign each pixel to one texture in the image, we apply the same clustering procedure previously described in section 2.2.3 but in this four-dimensional texture space.

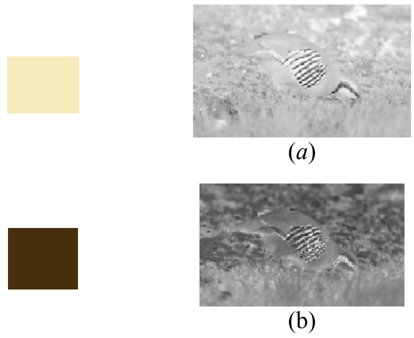


Figure 2: Two distance images obtained with CIEDE2000 color distance formulae, for the original image shown in Figure 1. Image (a) corresponds to light yellow and (b) to brown.

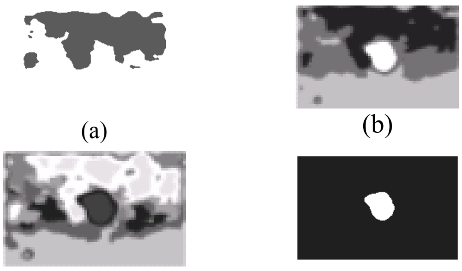
We again assume that, in natural scenes, the number of different textures is less or equal to 16. Once each pixel in the image has been classified, we select only those pixels whose texture is equal to the desired one, obtaining a black and white image in which white pixels are those with the desired texture, as shown in Figure 3. This image will be used afterwards in the region-growing process.

2.4 Multistep Region Growing

As explained before, region-growing techniques have two critical aspects: the seed selection and the choice of the merging condition.

2.4.1 Seed Selection

We must notice that those pixels more similar to the reference color have been assigned a high value (note that we have inverted the distance image). In order to select the seeds, the next three steps are followed for each of the distance images: 1) Selection of the local maxima of the image, which represent the candidates to seeds. Not all these candidates will be seeds for the region growing, because these local maxima do not belong necessarily to the region of interest. 2) Application of a threshold to these candidate seeds. The threshold is determined from the histogram of the distance following an algorithm developed by the authors (Acha et al, 2003). 3) Finally, texture information is applied to reject some of the seed candidates: the final seeds must have, not only the desired color, but also the desired texture. That is, among the group of color seeds, only those pixels that appear white in the texture image are selected.



(a) (b) (c) (d)

Figure 3: The original image in Figure 2 is processed in order to isolate the strips of the bird. Image (a) is the result of the k-means algorithm for k=2. The value of D is 0.6944. Image (b) is the result for k=4 and D=0.7469. Image (d) corresponds to k=8 and D=0.4304 finally, the maximum D value is obtained for k=4, which leads to the texture information shown on image (d).

2.4.2 Multistep Region Growing

We use a dynamic region growing method to segment the distance images. In an ordinary region growing, the merging condition is always the same. For each seed, the algorithm grows a region with a determined condition. With this multi-step technique, the merging condition automatically changes in order to find its optimum value, which will correspond to the highest value of the contrast parameter explained later on in this subsection.

Let us take a particular seed. The process begins with a region growing with three conditions:

1) Not belonging to another region grown before.

2) The texture of the pixel must be the desired one. That means that a pixel only will be added to the region if it has a value equal to one (for normalized values) in the texture image.

3) The new pixel must be similar to the pixels that already are in the region for all the distance images. This similarity is measured according to (4):

$$\frac{F_{\max n}+F_{\min n}}{2}-\tau \le F_{ij,n} \le \frac{F_{\max n}+F_{\min n}}{2}+\tau,\ n=1,\dots,N \qquad (4)$$

In equation (4), n is a subindex indexing the reference colors, N is the number of reference colors, $F_{max,n}$ and $F_{min,n}$ are the maximum and minimum values of the pixels in the distance image n inside the region, i and j are the coordinates of the pixel, F is the value of the pixel in the distance image n, and τ is the tolerance step, which will be iteratively increased. Once a region is grown with a particular τ, the next step is to verify whether the region obtained is optimal. If it is not optimal, the region growing will be repeated with a more relaxed condition, that is, τ is increased. More specifically, τ follows the expression:

$$\tau = \alpha \cdot \sigma_n \qquad (5)$$

In equation (5), σ_n is the standard deviations of the region in the distance image n grown before and α is variable with an initial value experimentally fixed to 0.1. For each iteration, to relax the condition and make the merging interval larger, we increase α by 0.1. Then, the region growing is repeated with this more relaxed condition.

The optimality criterion to choose the best region during the region-growing process consists in maximizing a contrast parameter. This contrast parameter is calculated for each distance image as:

$$contrast = \frac{\left|\overline{Inside\ edge} - \overline{Outside\ edge}\right|}{\overline{Inside\ edge} + \overline{Outside\ edge}} \qquad (6)$$

In (6) $\overline{Inside\,edge}$ and $\overline{Outside\ edge}$ represent the mean values of the pixels belonging to the inner border and outer border of a region respectively. We then, use the mean of so obtained contrast values to determine whether the region is the best or not

At the beginning, the region growing has a very restrictive merging condition. This will lead us to obtain a small region. While repeating the process, the contrast parameter of equation (6) is calculated. While the grown region is inside the object, the contrast parameter increases its value in a smooth way, because pixels belonging to the inner border and to the outer border of the region are similar. When the region whose contrast is being calculated matches the object, the contrast parameter has a high value because pixels surrounding the region will differ from those inside the region. If we continue growing, the contrast parameter will be low again because both the inner border and the outer border are similar. Therefore when the contrast parameter reaches its maximum we have obtained the best region. A steep slope in the contrast parameter evolution corresponds to those values of α for which boundaries are reached. Once the whole boundary is reached, if the tolerance is being enlarged again the region will exceed the limits of the object and, therefore, the contrast will decrease. In such a situation the region growing will stop because the stop condition has been attained.

3 EXPERIMENTAL RESULTS

In order to test the algorithm, we have performed the segmentation of ten particularly difficult images, with textures compound of very different colors. Some examples are shown in Figure. 4 To better analyze its performance, we have compared the algorithm with one previously published by the authors (Fondón et al,2006). This second algorithm takes as the reference color the centroid of the colors in the selection box. It leads to a poor segmentation result if colors within a texture are too different. That is why, as can be observed, segmented regions present holes in (e)-(h). This problem is solved in Figures (i)-(l).

Figure 4: Examples of segmentations. (a)-(d) Original images with the selected color and texture marked by the user in green. (e)-(h) Segmented images by the previous work. (i)-(l) Segmented images by the new algorithm.

4 CONCLUSIONS

An algorithm to segment multicolored textured image has been proposed. In a previous work (author's work 1) the reference color was the centroid of the colors present within the texture. In this case, the segmented regions could have holes corresponding to big differences between the reference color and that particular pixel color. In the present work, as we take into account all the colors in the region, these failures disappear achieving higher quality results. In the multi-step region growing technique, which has an automatic adaptable step, we use a set of color distance images, each one corresponding to a reference color and we apply an N-dimensional region-growing, where N is the number of color distance image. A contrast parameter is introduced to decide the optimum step for the region-growing.

The method is designed for general-purpose images and its good performance with images difficult to be segmented is demonstrated.

As we have already exposed, the algorithm has been validated with 10 multicolored textured images providing better results than the previous work. The holes are avoided and the regions have better quality.

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