Cluster-Based Unsupervised Color Image Segmentation

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Abstract: A new technique for unsupervised segmentation of color images is presented here, which is based on the anisotropic diffusion and extension of the well-know hard C-means clustering algorithm. We suggest exploiting the separability of color information, which is represented in a suitable color space such as CIE(Lab) space. The components in the 3D space are smoothed through anisotropic diffusion. During the smoothing, the edges of the image are preserved. A clustering algorithm, which overcomes the problem of depending on the initializations of hard C-means algorithm, is employed to segment them after diffusion. Finally, an experiment is demonstrated in the paper, which verifies effectiveness and robustness of the method.

Keywords: Color image, Unsupervised image segmentation, Anisotropic diffusion, C-means clustering

1. Introduction

Image segmentation is the process by which an original image description is partitioned into some meaningful regions. It is usually assumed that the objects or substantial parts of the objects are represented by regions that are homogeneous in some sense such as color, texture, or motion. This operation is usually preliminary to higher-level tasks such as object recognition, classification, and semantic interpretation. The segmentation techniques for monochrome images can be extended to segment color images using R, G and B or their transformations (linear/nonlinear). By comparison to gray level images, color images contain three times as much data. Therefore, their use allows us to get a much more robust segmentation independent of lighting conditions and a better accuracy with regard to the extracted regions. A lot of segmentation techniques have been proposed for color images [1][2].

In this paper we present a new technique for segmenting images on the basis of color information. The remaining parts of the paper are organized as follows. Color space translation and anisotropic diffusion-based smoothing approach is presented in Section 2. In Section 3, we introduce a new clustering algorithm for segmentation. Some experiment results are demonstrated in Section 4. Finally, Section 5 gives conclusions and future work.

2. Color space translation and anisotropic diffusion

The most common used RGB color space is suitable for color display, but is not good for color scene segmentation and analysis because of the high correlation among the R, G, and B components. Celenk [3] claims that it is desirable to use a color space possessing uniform characteristics, such as CIE(Lab), for segmentation. CIE (International Commission on Illumination) defines a set of primaries with positive color matching functions across the entire visible spectrum. The primaries, X, Y and Z are strictly imaginary and have no correspondence to any monochromatic wavelengths in the visible spectrum. The values of X, Y and Z can be computed by a linear transformation from RGB tristimulus coordinates.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.607 & 0.174 & 0.200 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 0.116 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (1)$$

The typical CIE(Lab) space, which we use here, can be obtained through nonlinear transformations of the X, Y and Z values.

$$\begin{cases} L = 25 * (100Y/Y_0)^{1/3} - 16 \\ a = 500 * \left[(X/X_0)^{1/3} - (Y/Y_0)^{1/3}\right] \\ b = 200 * \left[(Y/Y_0)^{1/3} - (Z/Z_0)^{1/3}\right] \end{cases} \qquad (2)$$

where (X_0 ,Y_0 ,Z_0) are X, Y, Z values for the reference white. The difference between two colors can be calculated as the Euclidean distance between two color points $P(L_1a_1b_1)$ and $P(L_2a_2b_2)$ in this space. The formula for the color difference is described by:

$$D_{1,2} = \sqrt{(L_1 - L_2)^2 + (a_1 - a_2)^2 + (b_1 - b_2)^2} \quad (3)$$

The ability to express color difference as perceived by humans in terms of Euclidean distance is very important to color segmentation. The CIE(Lab) space has approximately uniform chromaticity scale.

Let $I(x,y) : \Re^2 \to \Re^n$ represent the color data (normally n=3), and $l(x,y) : \Re^2 \to \Re^+$, $a(x,y) : \Re^2 \to \Re^+$and $b(x,y) : \Re^2 \to \Re^+$ its three components in CIE(Lab) space. The lightness signal $l(x,y)$ is embedded in a one-parameter family of "derived" images $l(x,y,t)$and smoothed by anisotropic diffusion [4].

$$\begin{aligned} \frac{\partial l(x,y,t)}{\partial t} &= -\alpha[l(x,y,t) - l(x,y,0)] \\ &\quad +\beta div\{f'[||\nabla l(x,y,t)||]\frac{\nabla l(x,y,t)}{||\nabla l(x,y,t)||}\} \end{aligned} \quad (4)$$

where ∇l represents the gradient vector of function l, div denotes the divergence, α and β are positive parameters which can balance the two terms on the right of (4). In order to preserve the edges, the function $f(\cdot)$ must satisfy the following conditions:

(i) $0 < \lim_{t\to 0}(f'(t)/2t) = M$;

(ii) $\lim_{t\to\infty}(f'(t)/2t) = 0$;

(iii) $f'(t)/2t$ is a strictly decreasing function.

In our experiment, we chose a non-convex function $f(x) = x^2/(1+x^2)$, which satisfies above conditions.

The following iteration algorithm is employed to get the solution of the formula (4):

$$\left\{ \begin{aligned} v(n+1) &= v(n) - \alpha \cdot [v(n) - l(x,y,0)] \\ &\quad +\beta.\frac{\Delta v(n)}{1+\|\nabla l(x,y,t)\|^2} \\ l(x,y,t+1) &= \lim_{n} v(n) \end{aligned} \right. \quad (5)$$

The values of parameters α and β are chosen to be 0.01 and 0.2 respectively in this paper.

The components of $a(x,y)$ and $b(x,y)$ are smoothed using the same method. By combining the three components, we get the smoothed color image with the edges preserved.

3. Clustering-based unsupervised segmentation

The points in the CIE(Lab) space, after the smoothing step of Section 2, have been conveniently represented as vectors in a vector set $X = \{x_1, x_2, \cdots, x_k\} \subset \Re^3$ and need now to be clustered. The literature of pattern recognition offers a number of different techniques for this task [5].

Based on some measure of similarity, the vector set X is separated into C subsets $X_j = \{x_1^{(j)}, x_2^{(j)}, \cdots, x_{n_j}^{(j)}\}$ respectively containing $n_j (j = 1, 2, \cdots, C)$ vectors, which represent the C class. In order to estimate the clustering quality, the expectation of the sum of the squared errors J is often defined as an objective function,

$$J(X,V) = \sum_{k=1}^{K} p(x_k) \sum_{j=1}^{C} p(v_j|x_k) \|x_k - v_j\|^2 \quad (6)$$

where $p(x_k)$ is a sampling probability, $V = \{v_1, v_2, \cdots, v_C\} \subset \Re^3$, $v_j, (j = 1, 2, \cdots, C)$, referred to as the cluster, is defined as the mean vector of the subset X_j, ie.$v_j = \frac{1}{n_j}\sum_{k=1}^{n_j} x_k^{(j)}$.

If the vector $x_k \in X_j$ is decided by the nearest-neighbor principle, ie. fully assigning the vector x_k to the nearest cluster, the conditional probability is as follows:

$$p(v_j|x_k) = \begin{cases} 1, & x_k \in X_j, \\ 0, & Otherwise. \end{cases} \quad (7)$$

and the formula (5) is the hard C-means algorithm, which is used in color image segmentation by L.Lucchese [6]. We give some randomness to the conditional probability in order to overcome the deficiency of depending on the initializations. Let $H = -\sum_{i=1}^{K} p(x_i) \sum_{j=1}^{C} p(v_j|x_i) \ln p(v_j|x_i)$ denotes the randomness. It becomes a conditioned optimization problem. By minimizing the following function

$$L = J(X,V) - \lambda H \quad (8)$$

one can get the cluster:

$$\begin{aligned} v_j &= \frac{\sum_{k=1}^{K} p(x_k)p(v_j|x_k)x_k}{\sum_{k=1}^{K} p(x_k)p(v_j|x_k)} \\ &= \frac{\sum_{k=1}^{K} p(v_j)p(x_k|v_j)x_k}{p(v_j)} \\ &= \sum_{k=1}^{K} p(x_k|v_j)x_k \end{aligned} \quad (9)$$

After clustering, we obtain the set V, containing a certain number C of representative points in the CIE(Lab) space. At each pixel, the smoothed color x_k is replaced by the nearest cluster v_j according to the formula as follows:

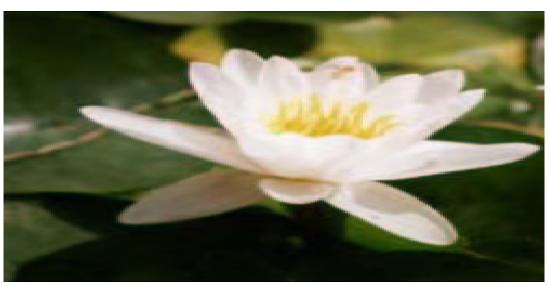
$$x_k = \arg\min_{v_j \in V} \|x_k - v_j\|^2 \quad (10)$$

The result of such an operation is a segmented color image in CIE(Lab) space, which can be shown as a set of regions coded by gray level or as the original image overlaid with the region boundaries. There are a lot of small regions in the final result which can be eliminated by a level-set based filter [7].

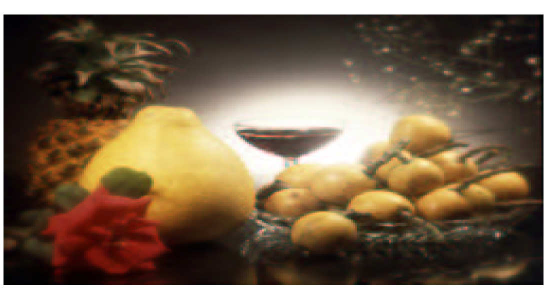
4. Experiment

All the algorithms described in the previous sections have been implemented in Microsoft Visual C++ under the operating system of Windows 2000 Server. We have tested our algorithms on a set of images. Figure 1 demonstrates some examples with various types of images in our experiment, which bear out the effectiveness of our method. Figure 1 shows the original images and Figure 2 shows the segmented results.

(a)

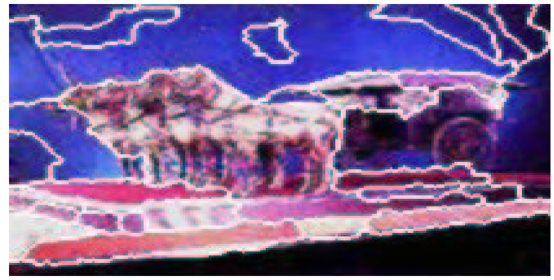


(b)



(c)

Figure 1: original images



(d)

(e)

(f)

Figure 2: the results of segmentation

5. Conclusion

We have demonstrated a new fully automatic method for segmenting color images. The color image first is translated to CIE(Lab) space. Its three components are smoothed by anisotropic diffusion, which is characterized by the preservation of the edges. The image is then segmented by a clustering algorithm, which is an improvement of hard C-means algorithm. The method proposed here increases the robustness and gets good results, but it has a deficiency of expensive computation. Future research will be focused on the reduction of computational complexity and the combination of color and feature information for image segmentation.

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