COLOR IMAGE SEGMENTATION USING DENSITY-BASED CLUSTERING

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ABSTRACT

Color image segmentation is an important but still open problem in image processing. In this paper, we propose a method for this problem by integrating the spatial connectivity and color feature of the pixels. Considering that an image can be regarded as a dataset in which each pixel has a spatial location and a color value, color image segmentation can be obtained by clustering these pixels into different groups of coherent spatial connectivity and color. To discover the spatial connectivity of the pixels, density-based clustering is employed, which is an effective clustering method used in data mining for discovering spatial databases. Color similarity of the pixels is measured in Munsell (HVC) color space whose perceptual uniformity ensures the color change in the segmented regions is smooth in terms of human perception. Experimental results using proposed method demonstrate encouraging performance.

1. INTRODUCTION

In order to facilitate practical manipulation, recognition, and object-based analysis of multimedia resources, partitioning pixels in an image into groups of coherent properties is indispensable—this process is regarded as image segmentation [1]. Hundreds of methods for color image segmentation have been proposed in the past years. These methods can mainly be classified into two categories: one is contour-based and the other is region–based [2]. Methods of the first category use discontinuity in an image to detect edges or contours in the image, and then use them to partition the image. Methods of the second category try to divide pixels in an image into different groups corresponding to coherent properties such as color etc., that is, it mainly use decision criteria to segment an image into different regions according to the similarity of the pixels.

Region growing and clustering are two representative methods of region-based segmentation [1]. Drawbacks of the region growing method are that it is difficult to make the growing or stop growing criteria for different images and the method is sensitive to noise. Recently, most researchers focus on treating the segmentation problem as an unsupervised classification problem or clustering problem [3-7]. In their methods, segmentation is obtained as the global minima of criterion functions associated with the fuzzy / possibilistic distance between the prototypes and the image pixels [7]. By partitioning pixels according to their global feature distribution, these methods achieve good global partitioning results for most of the pixels. But in these methods, spatial relationship of the pixels is rarely considered. The loss of spatial information of the pixels maybe leads to unreasonable segmentation results for that the pixels that are similar in low level feature (color etc.) but separate in spatial will be grouped into one region. And at the same time, run time complexity of this global partition is often high.

By regarding the image segmentation as the problem of partitioning pixels into different clusters according to their color similarity and spatial relation, we propose our color image segmentation method. It is a region-based method. According to the method, pixels in each segmented region should be connective in spatial and similar in color. Then, base on density-based clustering (DBSCAN), an approach to integrating the spatial connectivity and the color similarity simultaneously in the segmentation process is presented. By this approach, pixels in a color image will be grouped into different clusters, and these clusters form the final segmented regions of the image. Run time complexity of the method is low compared with that of the global cluster methods.

The remainder of the paper is organized as follows. Section 2 introduces density-based clustering. Section 3 describes our segmentation method in detail. Section 4 presents the experimental results. Conclusion and future works are given in section 5.

2.DENSITY-BASED CLUSTERING

In our method, spatial connectivity of the pixels is discovered by density-based clustering proposed by Ester in 1996 for discovering clusters in spatial database [8]. To prescribe our method, we give a briefly introduction to DBSCAN here.

The basic ideas of density-based clustering involve a number of new definitions. We intuitively present these definitions and then follow up with the introduction to the main idea of the algorithm.

Given a spatial dataset and objects in it distributes in a two-dimension space:

- The neighborhood within a radius of a given object is called the *Eps* of the object.

- If the *Eps* of an object contains at least a minimum number, *MinPts*, of object with similar property, then the object is called a core object.
- For the set of object, *I*, we say that object *p* is directly density-reachable from object *q* if *p* is within the *Eps* of *q*, and *q* is a core pixel (Fig. 1).
- Density reachability is the transitive closure of direct density reachability and this relationship is asymmetric. This asymmetric density reachability is density connectivity (Fig. 1).

DBSCAN searches for clusters by checking the *Eps* of each point in the dataset. If the *Eps* of a point *p* contains more than *MinPts*, a new cluster with *p* as the core object is created. DBSCAN then iteratively collects directly density-reachable objects from these core objects, which may involve the merge of a few density-reachable clusters. The process terminates when no new point can be added to any cluster.

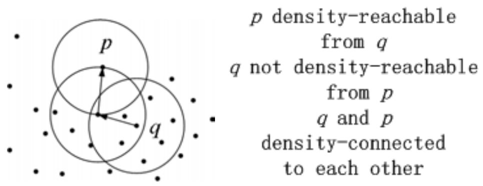


Fig. 1. Density-reachability and density-connectivity

Image can be considered as a special spatial dataset in which each pixel has a spatial location and a color value. Then, method used to discover clusters in spatial will be effective on discovering clusters in an image. Pixels which are similar in color and connective in spatial can be clustered together to form a segmented region. The difference between spatial clustering and pixel clustering is that image pixels distribute not only in spatial space, but also in other feature space such as color etc. Pixels that grouped into one cluster should not only connective in spatial but also be similar in color. Method to integrating color similarity and spatial connectivity will be presented in detail in section 3.

3. PROPOSED SEGMENTATION METHOD

In this section, the proposed image segmentation method is first described. Then the method to select relevant parameters is presented.

3.1 Using density-based clustering to find clusters (segmented regions) in an image

By reference to the definitions for DBSCAN in section 2 [9], we present these definitions and specifications for image segmentation and follow up with the process of our segmentation method.

- The spatial neighborhood of a given pixel is called the spatial *Eps* of the pixel. We name it *SpatialEps.*

SpatialEps is set as a circle in this paper. Fig 2. (a) illustrates the *SpatialEps* of a pixel *p*. The size of *SpatialEps* is the number of all pixels in the circle. Black points in the circle represent pixels which are color similar with *p*. Section 3.2.1 gives the statement of how to determinate parameters of a *SpatialEps*.

- The neighborhood in color space of a given pixel is called color *Eps* of the pixel. We name it *ColorEps.*

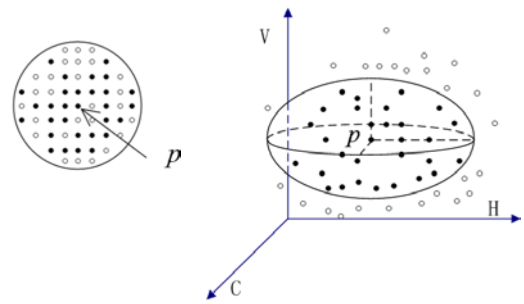
ColorEps is set as an ellipsoid in Munsell (HVC) color space in this paper. Fig 2. (b) illustrates the *ColorEps* of a pixel *p*. *ColorEps* is used to judge if pixels are similar in color with *p* or not. Pixels within the ellipsoid are color similar with *p* and pixels outside are color dissimilar with *p*. Section 3.2.2 gives detail statement of why we select Munsell color space and how to determine parameters of a *ColorEps* for an image according to its global color distribution.

- If the *SpatialEps* of a pixel contains at least a minimum number, *MinPts*, of pixels similar in color, then the pixel is called a core pixel. Its *SpatialEps* forms a core region.

When we are using density-based clustering to find clusters in an image, we need to know there how many pixels that are color similar with *p* in its *SpatialEps*. Then we project all the pixels in *p*'s *SpatialEps* to its *ColorEps*, if the number of pixels within the *ColorEps* is larger than *MinPts*, *p* is called a core pixel and its *SpatialEps* forms a core region.

- For the set of pixels in an image, *I*, we say that a pixel *p* is directly density-reachable from pixel *q* if *p* is within the *SpatialEps* of *q*, and *q* is a core pixel (Fig. 3).

Density reachability and density-connectivity for pixels have the same definitions as in section 2. The color similarity between color pixels is transitive as density reachability is transitive. Transmissibility of color similarity makes it possible that pixels that are gradually changing in color and connected in spatial will be clustered into the same region. This is consistent with human perception.



(a) *SpatialEps* (b) *ColorEps*

Fig. 2. *SpatialEps* and *ColorEps* of pixel *p*.

Based on the above definitions and specifications, we prescribe our segmentation method as follow.

1) Search the unlabeled pixels in an image in order for current core pixel and current core region. The order is from the top left corner to the bottom down corner of the image.
2) If a core pixel *p* is found, a new cluster is created. Then, we iteratively collect unlabeled pixels that

are density-connected with *p*, and Label these pixels with same cluster label.

3) If there are still existing core pixels in the image, goto 2).

4) For the pixels that are not included in any clusters, merge them with the cluster that is adjacent to them and has the highest similarity in average color value with them.

5) Label each cluster we find in the image as a segmentation region.

After the above segmentation process, pixels are put into different clusters and form different segmented regions of an image. The following section will present a method to determining the parameters of *SpatialEps* and *ColorEps* for an image.

3.2 Determining the parameters of *SpatialEps* and *ColorEps* for an image

In this section, we develop a simple and effective method to determine parameters of *SpatialEps* and *ColorEps*.

3.2.1. Determining the parameters of SpatialEps

There are two parameters for *SpatialEps* in each image, the size of the *SpatialEps* circle and the *MinPts*. We simply select the size of *SpatialEps* circle size according to the size of the image. That is, the larger an image is, the larger its *SpatialEps* circle will be. *MinPts* is set to half of the number of pixel in the *SpatialEps* circle, which means that we will consider the pixels whose color are same as the dominant color in the circle.

3.2.2 Determining the parameters of ColorEps

In this paper, *ColorEps* is formatted as an ellipsoid in Munsell (HVC) color space as shown in Fig 2. (b). Then, to determine the *SpatialEps* is to determine the length of the three radiuses of the ellipsoid H_{Radius}, V_{Radius} and C_{Radius}.

The reason why we select Munsell (HVC) color space is that it is perceptual uniform, which means that two color pairs, where a pair consists of two colors, that are equal in distance in a color space are perceived as equal in distance by viewer [10]. This perceptual uniformity can ensure that the color change in a segmented region of an image is smooth in terms of human perception. Good performance of content-based image retrieval in Munsell color space verified its efficiency [11]. Color transformation from RGB to HVC is not a linear one. Mathematical Transformation to Munsell (MTM) can be found in [12].

As defined in section 2, we say that a core pixel p_0 with color value (H_0, V_0, C_0) is color similar with pixel p with color value (H, V, C) when *p* lies in the color ellipsoid whose center is p_0. This can be described by function (1)

$$\frac{(H-H_0)^2}{{H_{Radius}}^2}+\frac{(V-V_0)^2}{{V_{Radius}}^2}+\frac{(C-C_0)^2}{{C_{Radius}}^2}\le 1 \qquad (1)$$

To determinate the value of H_{Radius}, V_{Radius} and C_{Radius}, we use the histogram concavity analysis method in H, V and C band respectively. Here we take the C band as an example.

Let's denote HS as the histogram of C color band as shown in Fig 3. By the meaning of histogram, we can intuitively think that each concavity on the HS represent a break of C color band in the image, which can be used to divide the pixels into different groups. Then, if there are n concavities in the HS, and D_i is the distance between the $(i)th$ and $(i+1)th$ concavities as shown in figure 3. In the *ColorEps,* C_{Radius} is set as the mean values of the distances as function (2)

$$C_{Radius} = \frac{1}{n}\sum_{i=0}^{n-1} D_i \qquad (2)$$

That is to say, two pixels can be considered as color similar with each other if their color distance is smaller than the mean value of the distances between adjacent concavities. Similar procedure can be used to determine H_{Radius} and V_{Radius}. In the three- dimension color space, we use the ellipse to judge if a pixel is color similar with the core pixel as function (1).

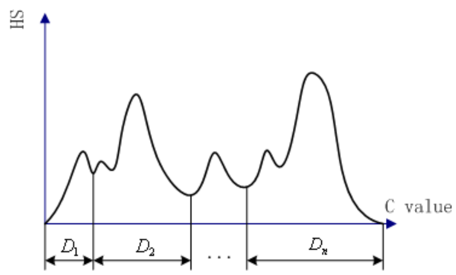


Fig. 3. Distance between adjacent concavities

By above process, parameters of *SpatialEps* and *ColorEps* for an image are determined.

4. EXPERIMENTAL RESULTS

To verify the proposed segmentation method, experiments were performed on images with different complexity on Pentium IV 1.5 GHz PC. It is take less than 1 second to segment an 200×200 image. As examples, Fig.4 gives six pairs of segmented color images (pepper, plane, mountain, tiger, hand and cameraman). In the example images, tiger is an image with texture region and cameraman is with noise.

Our method is not sensitive to noise and is effective to some of the textures, which is better than that of region growing methods [1]. Though texture is not considered in our method, as to image with texture, pixels in the texture region can be grouped together for that these pixels will be density-connected with each other with respect to the dominant color of the texture region. Our method would not produce segmented regions that are similar in color but separate in spatial, which is better than that of global cluster methods. For that an image is an ordered dataset from top left corner to bottom right corner, the average run time complexity of our method is $O(n \log n)$ which is same as that of density-based clustering [9].

5. CONCLUSION AND FUTURE WORKS

In this paper, a novel color image segmentation method is presented. The use of density-based clustering and the selection of Munsell color space have resulted in encouraging segmentation results. Future research will consider the following issues. First, more effective parameters determined method for *SpatialEps* and *ColorEps* should be considered. Second, texture descriptors should be integrated into segmentation process to improve the performance.

6. REFERENCE

[1] Milan Sonka, Vaclav Hlavac and Roger Boyle, *Image Processing, Analysis and Machine Vision*, Tomson Asia Pte Led, chapter 5, pp 123-124, 2002.

[2] Jitendra Malik, Serge Belongie, Thomas Leung and JianBo Shi, "Contour and Texture Analysis for Image Segmentation," *International Journal of Computer Vision* 42(1), 7-27, 2001.

[3] R.Krishnapuram and J.M. Keller, "The possibilistic c-means algorithms: insight and recommendations," *IEEE Trans, Fuzzy Systems*, Vol. 4, pp. 385-393, 1996.

[4] Jie Wei, "Image Segmentation Using Situational DCT Descriptors," *International Conference on Image Processing*, 2001,pp.738-741.

[5] K. Barnard, P. Duygulu, and D. forsyth, "Clustering Art," *Conference on Computer Vision and Pattern Recongniton*, Hawaii, pp. 434-441, 2001.

[6] Yining Dengm, B.S. Manjunath, "Unsuperivised Segmentation of Color-Texture Regions in Images and Video," *IEEE Transaction on Pattern Recongniton and Machine Intelligence*, Vol. 23, No. 8. August 2001.

[7] Tuan D. Pham, "Image Segmentation Using Probabilistic Fuzzy C-Means Clustering," *International Conference on Image Processing*, 2001, pp. 722-725.

[8] Martin Ester, Hans-Peter Kriegel, Jorg Sander, XiaoWei Xu, "A Density-Based Algorithm for Discovering Spatial Databases With Noise," *Proceedings of 2nd International Conference on Knowledge Discovery and Data Mining*, 1996.

[9] Jiawei Han, Micheline Kamber, *Data Mining Concepts and Techniques*, Morgan Kaufmann Publishers, Chaper 8, pp. 363- 364, 2001.

[10] Jia Wang, Wen-jann Yang and Raj Acharya, "Color Clustering Tecjmoqies for Color-Content-Based Image Retrieval from Image Databases," *International Conference on Multimedia Computing and System*, 1997.

[11] James D. Foley, Andries van Dam, Steven K. Feiner and John F. Hughes, *Computer Graphics: Principles and Practive*, 2nd ed., Reading, Mass, Addision-Wesley, 1990.

[12] M. Miyahara and Y. Yoshida, "Mathematical Transform of (R, G, B) Color Data to Munsell (H, V, C) Color Data," *SPIE Visual Communications and Image Processing*, vol. 1001, pp. 650-65, 1988.

Fig. 4. Image segmentation results by proposed method