Segmentation on Color Images Based on Watershed Algorithm

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Abstract

This paper presents a scheme for color image segmentation based on watershed algorithm that solves over-segmentation problem. A lexicographical order is adopted on HSI (Hue-Saturation-Intensity) color model so that morphological operations can be applied on color images directly. A marker image is then defined using both chromaticity and intensity information of the image. Together with multi-scale gradient image and marker image, watershed segmentation can make sure to partition image into meaningful objects and avoid further segmentation of homogeneous regions.

The results of the proposed algorithm are compared with those of other standard methods. Preliminary experiments have shown a better result and indeed solved over-segmentation problem.

1. Introduction

Segmentation is very important as a preprocessing for many image analysis and computer vision tasks ranging from medical image processing, industrial quality control, to robot navigation. Popularity on multimedia recently brings a huge amount of color images to our daily life making segmentation on color images an even more important issue. An ideal segmentation should correspond well with the physical objects depicted in the image such that object contours are closed and no dangling edges exist. Watershed segmentation exactly is an algorithm that fulfills the requirement. Not only it gives meaningful image segmentation but also it is sufficiently fast for most applications. However, watershed segmentation suffers a problem of over-segmentation due to many irrelevant local minima.

Watershed algorithm is based on morphological operation. Initially morphology dealt with binary images only, and basic operations were dilation and erosion. Natural extension using max and min operations brings morphologic transformations from binary image processing to gray scale processing. However, the extension of the concepts of binary and grayscale morphology to color images is not straightforward. When such techniques are applied independently to each primary color component of the image, there is a possibility for loss or corruption of information of the image due to high correlation among R-, G-, B-components of the image.

In this paper we have devised a color image segmentation technique based on watershed segmentation that applies morphological operations on color images directly and solves over-segmentation problem. The rest of the paper is organized as follows. Section 2, the lexicographical order on the HSI color model is introduced. Then a preprocessing of color image for smoothing is carried out through closing by partial reconstruction. In Section 3, a color gradient image is produced from the simplified image (from Section 2) using multi-scale gradients then followed by eliminating irrelevant minima. In Section 4, a marker image is obtained from the

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simplified image. In Section 5, combining the gradient image and the marker image, watershed algorithm is applied. A number of examples are provided in Section 6, and finally, conclusions are stated in Section 7.

2. Color Morphology and Simplified Image

The conventional way to represent color images is by red-green-blue (RGB) components. However, this type of representation has some drawbacks. Since RGB components are highly correlated and therefore, chromatic information is not directly fit for use. Instead, the HSI color space has been chosen for it is intimately related to the way in which human beings perceives color.

In order to apply morphological transformations on color images we need a way to order colors so that "min", "max" can be performed among different colors. Any pixel with color (h, s, i) on HSI color system will be treated as a vector, and the vector ordering scheme is defined [1] as follows:

(i) Initially, vectors are ordered with respect to the third component I. More specifically, they are sorted from vectors with the smallest I to vectors with the greatest I.

(ii) Vectors having the same value of I are ordered with respect to the second component S. Particularly, they are sorted from vectors with the greatest S to vectors with the smallest S.

(iii) Finally, vectors that have the same value of S and I are ordered with respect to the H component. More specifically, they are sorted from vectors with the smallest H to vectors with the greatest H .

Now we can extend the vector ordering procedure to color morphology. Let the set f to be a color image with pixel values in the HSI color space and the set g to be the structuring element (SE) for the vector morphological operations. The vector erosion and vector dilation can be described as[1]:

Vector erosion:

$$(f \Theta g)(x) = \wedge\{f(z) - g_x(z)\}$$

$$for \quad z \in D[f] \cap D[g_x]$$

Vector dilation:

$$(f \oplus g)(x) = \vee\{f(z) + g_{-x}(-z)\}$$

$$for \quad z \in D[f] \cap D[g'_{-x}]$$

where

$$f(k) + g(k) = (h_{kf} + h_{kg}, s_{kf} + s_{kg}, i_{kf} + i_{kg})$$

$$f(k) - g(k) = (h_{kf} - h_{kg}, s_{kf} - s_{kg}, i_{kf} - i_{kg})$$

with the restrictions that

if $h_{kf} + h_{kg} > 360$ then $h_{kf} + h_{kg} = 360$

if $s_{kf} + s_{kg} > 1$ then $s_{kf} + s_{kg} = 1$

if $i_{kf} + i_{kg} > 255$ then $i_{kf} + i_{kg} = 255$ and

if $h_{kf} - h_{kg} < 0$ then $h_{kf} - h_{kg} = 0$

if $s_{kf} - s_{kg} < 0$ then $s_{kf} - s_{kg} = 0$

if $i_{kf} - i_{kg} < 0$ then $i_{kf} - i_{kg} = 0$

In the following discussions we use a notation SE_n to represent a square structuring element of size $(2n+1)$x$(2n+1)$. For ease of segmentation, images are first simplified. In order to smooth the interior of the object and preserve the boundary of the object at the same time, we use closing by partial reconstruction to simplify the original image f. First, $\varphi_k(f)$, a closing with an SE_k on f, is used as the reference image, and $\delta_n(f)$, an dilation with SE_n, on f is used as the marker image:

$$\varphi^{(rec)}(\delta_n(f), \varphi_k(f)) \qquad 0 \le k \le n$$

In our experiment, we use $\boldsymbol{k} = 1$ and $\boldsymbol{n} = 2$.

3. Morphological gradients

The morphological gradient G(f) with a SE_n is defined as $\delta_n(f)$ - $\varepsilon_n(f)$. In order to detect ramp edges and avoiding the found edges being thick and/or merged, we need an SE of large

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size for the former and an SE of the small size for the latter. In order to overcome this problem, a multi-scale gradient,

$$MG(f) = \frac{1}{n}\sum_{i=1}^{n}\left[\varepsilon(\delta(f, SE_i) - \varepsilon(f, SE_i), SE_{i-1})\right]$$

MG(f), operator is used [8]:

where SEi is a SE of size $(2i+1)$x$(2i+1)$.

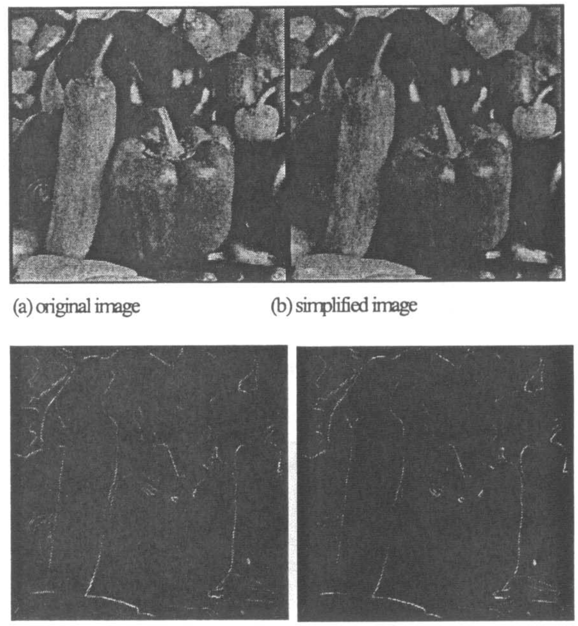
Because of noises and quantization error within homogenous regions producing many irrelevant minima in the resulting gradient images, which cause over-segmentation later in the process of watershed algorithm. Hence, we use a dilation with a small SE B of size 2x2 on (*MG(f)*), i.e. (*MG(f)*⊕B), to eliminate irrelevant minima [2]. To further remove the local minima with low contrast, a constant h is added to the gray value of the dilated gradient image. Then the local minima with a contrast lower than h can be filled using the reconstruction by erosion of MG(*f*) from (MG(*f*))⊕B + h [2]. The final gradient image, FG(*f*), can be expressed as

$$FG(f) = \phi^{(rec)}[(MG)(f) \oplus B + h, MG(f)].$$

In our experiment, h is determined as the value of 35 percentile of the histogram on gray image of (*MG(f)*⊕B). In Fig. 1, comparing (a), (b), we can see that the shapes of peppers remain the same but the details of stalks in (b) are not as much as in (a), similarly, in (d), it does not have so much detailed variances as in (c).

4. Marker Extraction

Markers are used to locate roughly where objects and background connected components are. In order to make sure that the interior of an object will be kept as a whole, the extracted markers will be imposed on the FG(*f*) as minima and suppress all other gradient minima. To obtain the marker image M(*f*), we do histogram analysis with respect to H, S, I. For each histogram, after smoothing, it is divided into several homogeneous regions according to their peaks and valleys. The resulting marker image M(*f*) is a binary image such that a pixel is a marker (to be black) if it belongs to a homogeneous region in one of the H-, S-, or I-histogram, and, on the other hand, a pixel will be white if it is not yet belonging to any regions. Thus the marker image contains a set of black pixels, i.e. markers, marking the core regions, and a set of white pixels remaining unassigned to any regions.



(a) original image (b) simplified image

(c) MG(*f*) (d) FG(*f*)

Figure 1. The procedure of obtaining the final gradient image.

(a) M(*f*) (b) C(*f*)

Figure 2. M(*f*) and C(*f*).

As in the Fig. 2(a), we can see that most of marker pixels appear as one connected component inside one object and background as we expected.

5. Watershed algorithm

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To apply watershed algorithm, we define an image C(*f*) as the combination of marker image M(*f*), and the final gradient image FG(*f*). For any pixel **p** at the position (*i,j*) :

$$C(f)(p) = \begin{cases} FG(f)(p) & p \text{ is black in } M(f), \\ \frac{1}{2}(FG(f)(p) + M(f)(p)) & p \text{ is white in } M(f). \end{cases}$$

Since M(*f*) is a rough partition of objects, we take values of FG(*f*) for those markers to avoid over-merging, and the average values for those non-markers to preserve the contour of objects depicted in the image. C(*f*) is shown in Fig. 2(b). Finally, to further remove noise, an anisotropic median diffusion filter [6] is applied on C(*f*) then watershed algorithm is applied. The resulted image is shown in Fig.3. As it shows, C(*f*) can ensure that both interior and contour of an object will be detected as it should be.

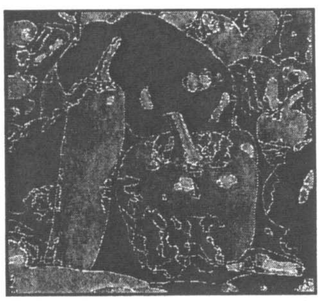

Figure 3. Result after applying watershed.

6. Experimental results

In most of cases, the above-mentioned algorithm based on watershed algorithm produce meaningful image segmentations. However, Some may require further merging of regions. For region merging, we use color information to define similarity criteria between regions. For every region, to compute the averaging intensity and averaging hue, the merging condition is

$$I_{th} = \min(I_{\max}, (I_0 + C \times \left\lfloor \frac{1}{\Delta h} \right\rfloor)) \qquad 0.006 \le \Delta h \le 0.008$$

$$I_{th} = I_{\max} \qquad \Delta h < 0.006$$

In here, hue is normalized to [0~2], and parameters I_{max}, *c* and I_0 are set to be 20, 0.28 and 7. Δh is the difference of the average hues between two regions. For any two neighboring regions, if their averaging hue difference is within 0.008, and the difference of the average intensity is smaller than or equal to the threshold I_{th} then these two regions will be merged. After a merging occurs, update the region label, region size and recomputed the new averaging hue and intensity.

6.1. Synthetic images

The first experiment uses synthetic ideal step color image (Fig.4(a)) since it allows objective performance measuring. Our method is applied on Salt-and-pepper noised image and Gaussian noise with standard deviation 15 added respectively (Fig.4 (a) and (b)). Two methods are adopted for comparison. Method 1 is the conventional watershed segmentation method, which first transform color image into gray scale image, then apply watershed algorithm. Method 2 is inspired by Gao's method [3] to use gradient information in both intensity and chromatics. In this method, Sobel edge detector on gray scale image as well as color gradient (: δ(f) -ε(f)) are obtained, then do point-wise maximum to form the final gradient image for watershed algorithm. Fig. 5 and 6 illustrate the results. It is obviously that our method performs the best among three methods.

6.2. Natural scenes

Experiments are performed on some common color images for further testing. In Fig. 7, (a) is our method, if we apply merging procedure on (a), we can see that in (b) the number of segmented areas on the bushes and the lower right corner of the lawn become less. However, comparing (c) and (d),

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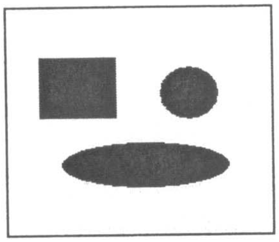
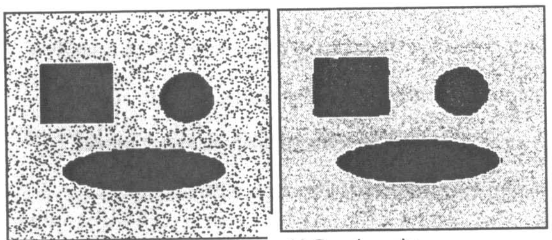
our method performs well enough even without merging.

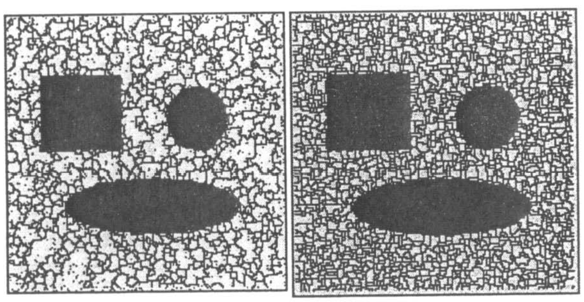


(a) Synthetic color image



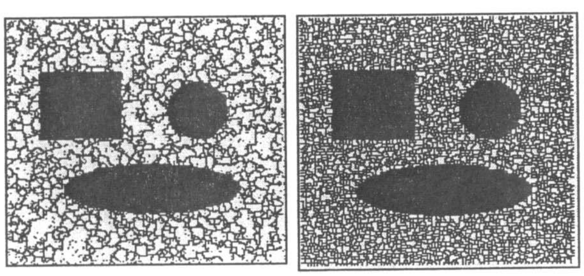
(b) Salt-and-pepper noise (c) Gaussian noise

Figure 4. Images for testing and (b) (c) are segmented results (in white lines) with our method.



(a) Salt-and-pepper noise (b) Gaussian noise

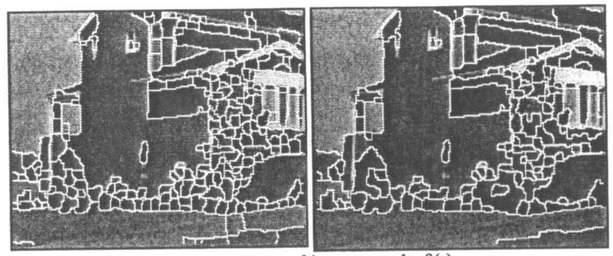
Figure 5. Segmentation results by method 1.



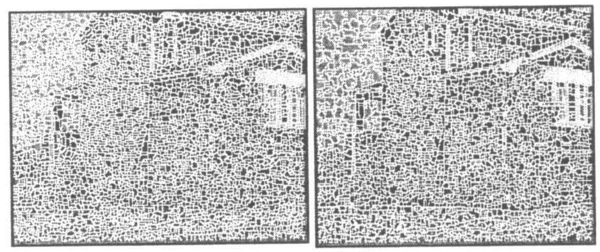
(a) Salt-and-pepper noise (b)Gaussian noise

Figure 6. Segmentation results by method 2.

that there are some unexpected noises. Fig. 8 shows the results using our method.

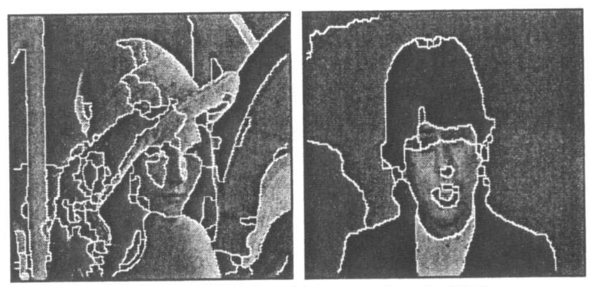


(a) our method. (b) merge result of (a)



(c) method 1. (d) method 2

Figure 7. "House" image for testing.



(a) segmented result of Lenna (b) segmented result of Calire

Figure 8. More results using our method.

7. Conclusion

In this paper, an unsupervised segmentation on color images based on watershed algorithm has been presented. As demonstrated, this segmentation technique is robust to noises and effectively solves the problem of over-segmentation. The performance of watershed-based segmentation method largely depends on the gradient image used in the method. We use both color and intensity information, combining marker and multi-gradient to form a gradient image for watershed segmentation, and obtain a very satisfying result.

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