A modified region growing algorithm for multi-colored image object segmentation

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A hybrid algorithm based on seeded region growing and k-means clustering was proposed to improve image object segmentation result. A user friendly segmentation tool was provided for the definition of objects, then k-means algorithm was utilized to cluster the selected points into k seeds-clusters, finally the seeded region growing algorithm was used for object segmentation. Experimental results show that the proposed method is suitable for segmentation of multi-colored object, while conventional seeded region growing methods can only segment uniform-colored object.

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Image segmentation is an essential process for most intelligent image and video analysis tasks, the region growing is one of the most fundamental methods used in image segmentation. Research on region growing, however, has focused primarily on the design of feature measures and on growing and merging criteria. Adams *et al.*[1] proposed seeded region growing (SRG) which based on the conventional region growing postulate of pixels similarity within regions. SRG is controlled by choosing a number of pixels, known as seeds. For a good segmentation, it is required that the regions have relative uniform color and the seed pixels have a gray value which is typical of the region. The result of SRG will go awry if the initial seed falls on a noise point, moreover, SRG has an inherent dependence on the order in which the points and regions are examined[2]. Wan *et al.* reported symmetric region grow (SymRG)[2] that is insensitive to the points' examining order and the initial seeds selection. Xu *et al.*[3] proposed integrated approach based on log Gabor wavelets edge detection, k-means and SRG method to improve natural color image segmentation result, but the approach has shortcomings of heavy computation load and the result has poor semantic meaning to human vision.

Since the ill-defined nature of image object semantic homogeneity, at present, efficient algorithms on fully automatic object segmentation only can be used in some types of object segmentation with prior knowledge, a more practical solution is the interactive segmentation[4]. Recently, these techniques were studied by Maxwell[5,6] *et al.*, the methods may work well on certain images, but generally they are sensitive to noise, pixel growing order and selection of initial seeds.

A desirable image segmentation method should be able to get from natural image, one or more semantic meaningful object(s) which generally contain multi-homogeneity regions, be robust to noise and user selection of initial seeds. Our method meets most of these requirements and can be used in the most of general applications.

At the first stage, we provide a mouse-based point-and-click mechanism for user to draw a line on the interested object, as shown in Fig. 1.

The k-means algorithm was then used to find the seeds-clusters on the selected line. Suppose pixels gray values on the selected line were

$$\Omega = \{p_1, p_2, \cdots, p_m\}, \quad 0 \le p_i \le 255, \quad 1 \le i \le m, \quad (1)$$

where m is the number of pixels on selected line. To determine the initial clusters number K, we use a modified version m-bin histograms[7] technique as following. 1) Sort Ω by min-max order, we have

$$\Omega' = \{p'_1, p'_2, \cdots, p'_m\}. \quad (2)$$

2) Get clusters number K and seeds' initial centers $Q = \{q_1, q_2, \cdots, q_k\}$ by

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k = 1; q_k = p_1
for i = 1 to m
  for j = 1 to k
    if (p'_i − q_k) > T_bin then
      k = k + 1, q_k = p'_i
    end
  end
end
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where $1 \le k \le K$, T_{bin} is the bin width of m-bin histogram[7]. 3) Then the seeds' final centers $Q' = \{q'_1, q'_2, \cdots, q'_k\}$ are determined by minimizing the squared-error distortion from each associated cluster center, the iteration stops if the cluster centers are stable and finally the centers is obtained[8,9].

Each center q'_k and cluster's member Ω_k can be found by

$$\Omega_k = \{p_i | p_i \in \Omega', (p_i - q'_k) < T_{\text{bin}}\}. \quad (3)$$

Each threshold δ_k in cluster Ω_k is

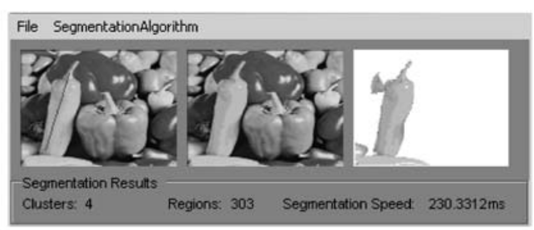

Fig. 1. User interface of the proposed method.

Table 1. Comparison of Segmentation Results by Different Algorithms

Algorithm	SRG	Watershed	Our Method	Our Method	Our Method
Image Name	a	b	c	d	e
Image Resolution	400 × 300	400 × 300	400 × 300	200 × 200	200 × 200
Colors on Object	1	–	4	4	5
Regions	1	59	532	303	309
Speed (ms)	78.125	359.375	312.5	230.3312	220.3168
Robust to Noise	Weak	None	–	–	Strong
Segmentation Results Semantically Meaning	No	No	Yes	Yes	Yes

$$\delta_k = \max|p_i - q'_k|, \ p_i \in \Omega_k. \quad (4)$$

Suppose there are N_k pixels in cluster Ω_k. The dominant seeds cluster $\Omega_{\rm d}$ will be found by

$$N_{\rm d} = \mathrm{Max}(N_k), \quad k = 1, 2, \cdots, K. \quad (5)$$

The noise seeds cluster $\Omega_{\rm n}$ can be found by

$$N_{\rm n} = \mathrm{Min}(N_k), \quad k = 1, 2, \cdots, K \text{ and } \frac{N_{\rm n}}{m} < T_{\rm n}, \quad (6)$$

where $T_{\rm n}$ is the noise level threshold, it is determined by noise distribution on the image.

At the second stage of image segmentation, we conduct SymRG based on the work of Wan *et al.*[2] and others[1,10−12].

Suppose image is of size $W \times H$, and gray value of pixel $p(i,j)$ is g_{ij}^k, the superscript k means that the seed belongs to seeds cluster Ω_k, we examine its 8 connected neighboring pixels and do region growing.

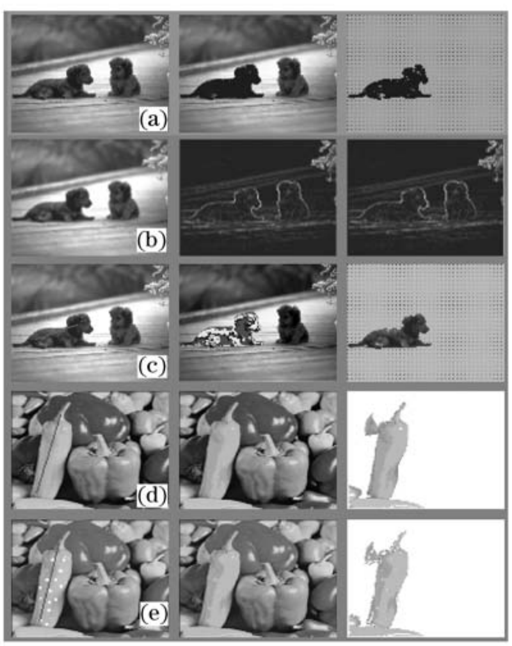

Fig. 2. Segmentation results. (a) Seeded region grow (SRG) algorithm, 1 region in 78.125 ms; (b) watershed algorithm, 59 regions in 359.375 ms; (c) the proposed algorithm, 4 seeds-clusters, 532 regions in 312.5 ms, $\delta_k = 8$; (d) the proposed algorithm, 4 seeds-clusters, 303 regions in 230.3312 ms, $\delta_k = 8$; (e) the proposed algorithm, robust to noise, 5 seeds-clusters, 309 regions in 220.3168 ms, $\delta_k = 8$.

1) If $p(i,j) \in \Omega_k$, the gray value distance with its 8 neighboring pixels d_{mn} is determined by

$$d_{mn} = |g_{mn} - g_{ij}^k|, \begin{cases} 1 < i < H, \ 1 < j < W \\ i-1 \le m \le i+1 \\ j-1 \le n \le j+1 \\ m \ne n \end{cases}, \quad (7)$$

which describes the similarity between seeds and its neighboring pixels. 2) If $d_{mn} < \delta_k$, then we label $p(i,j)$, grow the labeled region to $p(m,n)$, and update the currently growing center with $p(m,n)$, where δ_k was determined by Eq. (4). 3) If $p(i,j) \in \Omega_{\rm n}$, where $\Omega_{\rm n}$ is noise cluster, then the noise pixel is removed by replacing its gray value with the values of other seeds nearest to the noise pixel, then go to step 1) and repeated again. 4) Iteratively do step 1) to step 3) until no similar pixels are found.

In experiment, we use images that have been widely adopted in literatures such as in Ref. [13]. We compare the method with the latest SRG[2], watershed[14,15] algorithms in the robustness to noise, semantic meaning, region numbers, speed and segmented-colors, the results were shown in Fig. 2 and Table 1. We can see that proposed method is faster than watershed, more meaningful to human perception, and can segment more colored-regions than SRG and watershed.

In summary, we proposed a hybrid interactive image object segmentation method based on seeded region growing and k-means clustering. It is more flexible, powerful, robust than most of the latest methods such as SRG[2] and watershed[14,15], more importantly, it is suitable for segmentation of multi-colored object, while conventional seeded region grow methods can only segment single-colored object.

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