IEICE Proceeding Series

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Vol. 1 pp. 90-93
Publication Date: 2014/03/17
Online ISSN: 2188-5079

2012 International Symposium on Nonlinear Theory and its Applications
NOLTA2012, Palma, Majorca, Spain, October 22-26, 2012

Interactive Segmentation for Color Image based on Visual Saliency

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Abstract– The problem of efficient, interactive image segmentation in still image is of great practical importance in image editing. Recently, an approach based on optimization by graph-cut has been developed. However, interactive image segmentation approach which is intuitive and efficient to users is required. In this paper, we proposed novel interactive image segmentation method based on visual saliency. In this method, a user provides only some foreground pixels as seeds. Image segmentation is performed by optimizing proposed graph by using the graph-cut algorithm. In addition, in order to achieve an efficient segmentation, concept of neighborhood is extended to long-range neighborhood.

1. Introduction

Image segmentation is a technique for extracting an object (foreground) in an image from its background. The segmentation result can be employed for pre-processing of many practical applications, such as pattern recognition, image editing and so on. However, foreground/ background segmentation of photographs is an inherently ambiguous problem. Since automatic segmentation is still far from practical use, most segmentation algorithm rely on user interaction to provide more constraints for the segmentation.

Among several types of user interaction paradigms that have been investigated and implemented, the bounding box interaction is, arguably, the most natural and one of the most economical in terms of the amount of user interaction[1-3]. Lempitsky et al. [1] proposed a new approach that uses the tightness prior of the bounding box, which assumes that the desired segmentation should have parts sufficiently close to each side of the bounding box. However, their algorithm is very slow due to its mathematical complexity. Many approaches, such as GrabCut [4], use an objective function that includes appearance model as an unknown variable. The segmentation and appearance are optimized alternatively, in an expectation maximization manner. But, this approach may get stuck in a local minimum. On the other hand, Stauffer et al. [5] proposed other interactive approach that a user provides some foreground and background pixels as seeds. In this method, color likelihoods of background and foreground are calculated by optimizing Gaussian Mixture Model (GMM) parameters based on seed pixels. Pham et al. [3] presented an efficient algorithm foe interactive image segmentation with a user supplied object bounding box. However, interactive image segmentation approach which is intuitive and efficient to users is required.

In this paper, we proposed novel interactive image segmentation method based on visual saliency. First, a user provides only some foreground pixels as seeds. Secondly, foreground likelihood is calculated by optimizing GMM parameters. On the other hand, background likelihood is calculated based on visual saliency. Finally, image segmentation is performed by optimizing proposed graph by using the graph-cut algorithm. In addition, in order to achieve an efficient segmentation, concept of neighborhood is extended to long-range neighborhood.

The rest of this paper is organized as follows. Section 2 presents our interactive segmentation method. In section 3, discusses experimental results. Section 4 concludes the this paper.

2. Proposed method

2.1. Outline of proposal algorithm

The procedure of proposed method is shown in Fig. 1.

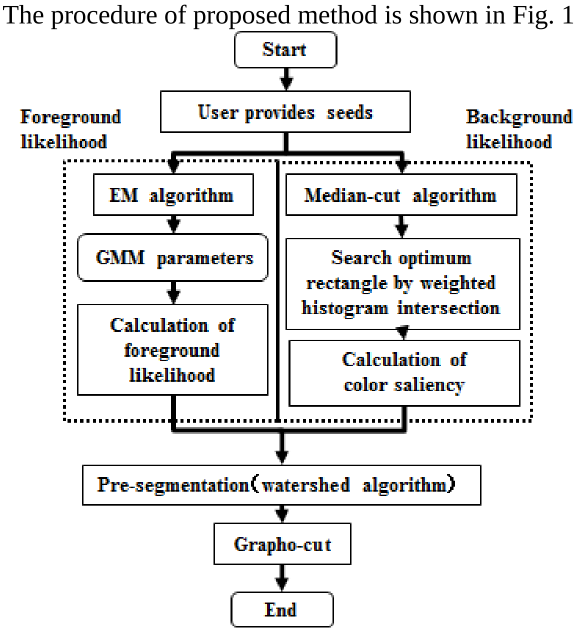


Fig. 1 The procedure of proposed method

First, a user provides only some foreground pixels as seeds for segmentation. Our interactive approach is a concept that is intuitive and efficient to users compared with conventional approach, and it requires only one mouse click and short movement to specify it.

2.2. Foreground likelihood

In this section, we describe calculation of foreground likelihood based on provided seed pixels. The concept of our foreground likelihood is similarity of color between each pixel and seeds. To calculate the similarity, GMM is optimized by using the Expextation Maximization (EM) algorithm. In this study, since imputed image *I* is expressed 24 bit RGB color, foreground likelihood is defined by:

$$\Pr(I_p \mid S) = \sum_{i=1}^{K} \alpha_i p_i (I_p \mid \mu_i \Sigma_i) \quad (1)$$

$$p(I_p \mid \mu, \Sigma) = \frac{1}{(2\pi)^{3/2} |\Sigma|^{1/2}} \cdot \exp\left(\frac{1}{2} (I_p - \mu)^T \Sigma^{-1} (I_p - \mu) \right) \quad (2)$$

where I means seeds, I_p is each color (RGB) intensity of pixel p, K is the number of mixtures, α is the weight, μ is average, and $\sum$ is variance-covariance matrix.

2.3. Background likelihood

In the proposed approach, seeds concerning background are not provided by a user. Therefore, background likelihood is calculated from visual saliency map created by foreground seeds.

In this paper, visual saliency is obtained from color saliency map proposed by Inoue et al. [6]. Firstly, initial rectangle $R' = (i, j, m, n)$ is created on the basis of provided seeds. Here, parameters (i, j) are x and y coordinates, (m, n) are width and height of rectangle, respectively. Then, the number of colors in an original image I are reduced by the median-cut algorithm. As a result of color reduction, the number of colors is C. A frequency of each color component is $\tilde{h}_c$ $(c \in \{1, \dots, C\})$, color histogram is $\tilde{h} = [\tilde{h}_1, \tilde{h}_2, \dots, \tilde{h}_C]$. Here, $\tilde{h}$ is normalized by $h_c = \tilde{h}_c / \sum_{c'=1}^{C} \tilde{h}_{c'}$. The weighted histogram intersection is defined by:

$$s_w(h^I, h^O; w^I, w^O) = \sum_{c=1}^{C} w_c^I w_c^O \min\{h_c^I, h_c^O\} \quad (3)$$

where h^I and h^O are normalized histograms in inside and outside of rectangle, w^I, w^O are weight vector for each histogram. in order to contain important object for a user, the initial rectangle *R*' is optimized by solving following minimization problem:

$$\min_R \quad s_w(h^I(R), h^O(R); w^I(R), w^O(R)) \quad (4)$$

where weight vectors for rectangle $R' = (\tilde{\imath}, \tilde{\jmath}, \tilde{m}, \tilde{n})$ are defied by:

$$w_c^I(R) = h_c^I(R) \quad (5)$$

$$w_c^O(R) = \begin{cases} h_c^O(R)^{-1}, & if \quad h_c^O(R) > \varepsilon \\ 1, & otherwise \end{cases} \quad (6)$$

After the optimization of rectangle, background likelihood of pixel (a, b) is obtained by:

$$S_{ab}^O = \frac{\tilde{h}_{cab}^O(R)}{\tilde{h}_{cab}^I(R) + \tilde{h}_{cab}^O(R)} \quad (7)$$

2.4. Graph cut

In this paper, image segmentation is performed by optimizing proposed graph by using the graph-cut algorithm. The structure of proposed graph *G* is shown in Fig. 2. The proposed graph *G* includes some nodes corresponding to pixels of image *I*. There are two additional terminal nodes (foreground: *s*, background: *t*). as first, G consists of only two types of edges, which are neighborhood links (n-link) and terminal links (t-links). Each pixel has two t-links, {s, i} and {i, t}, connecting it to each terminal. Each pair adjacent pixels {i, j} is connected by an n-link. The n-link of (ni, nj) is defined by:

$$\lambda \frac{e^{-\|C_i - C_j\|} + \varepsilon}{1 + \varepsilon} \quad (8)$$

where C_i and C_j are color vectors of each node, λ is weight parameter, ε is slight value. The capacities of all edges are initialized in Tab. 1.

In addition, we modify the proposed graph to involve the extended neighborhood. The concept of the extended neighborhood is shown in Fig. 3. We add a new type of edge which is extended neighborhood links. This link connects all pixel pairs that are within the long-range neighborhood $\|P_i - P_j\| < T_d$ and have similar colors $\|C_i - C_j\| < T_c$, where $\|\cdot\|$means the Euclidean distance, P is coordinates in 2D image plane, C_i and C_j are color vectors in LAB color space, . For each extended neighborhood link, we add θ to its capacity. Thus, extended neighborhood links are defined by:

$$EN_{ij} = \begin{cases} \theta & if(\|C_i - C_j\| > Tc) \\ 0 & otherwise \end{cases} \quad (9)$$

The proposed graph construction can produce a high quality segmentation. However, improvement of segmentation by eliminating redundancies is required. We perform pre-compute image over-segmentation to create a new graph where the nodes are instead the segmented regions. For this pre-segmentation, the watershed algorithm [7] is employed. For calculation of each link in proposed graph, mean color of each region is used. Finally, the max-flow algorithm [8] is employed to solve the minimum cut problem for image segmentation.

Tab. 1 The capacities of all edges

Edge	Cost	For
(n_i, n_j)	$\lambda \dfrac{e^{-\lVert C_i - C_j \rVert} + \varepsilon}{1 + \varepsilon}$	$(i, j) \in N$
(s, n_i)	$-\ln \Pr(I_p \mid O)$	$i \notin seed$
	K	$i \in seed$
(n_i, t)	$\dfrac{\tilde{h}^{O}_{cij}(R)}{\tilde{h}^{I}_{cij}(R) + \tilde{h}^{O}_{cij}(R)}$	$i \notin seed$

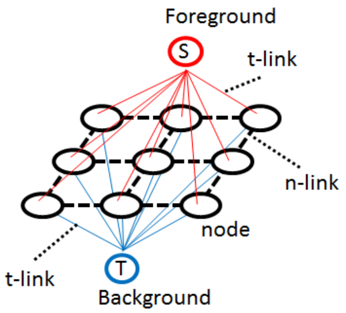


Fig. 2 The sample of graph structure with two terminal nodes

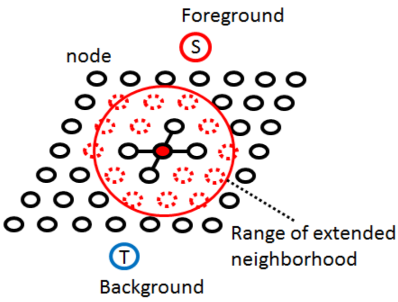
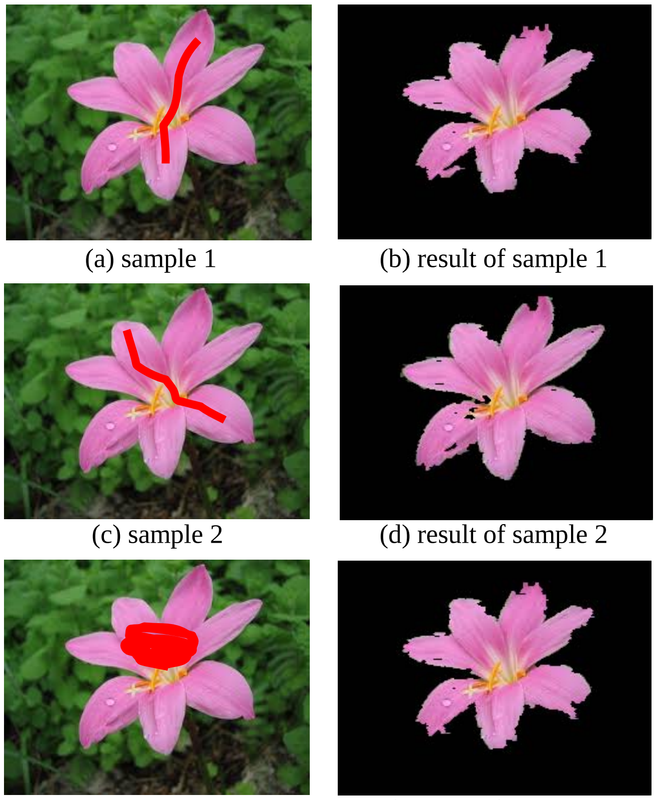


Fig. 3 The concept of extended neighborhood



(a) sample 1 (b) result of sample 1

(c) sample 2 (d) result of sample 2

(e) sample 3 (f) result of sample 3

Fig. 4 Robustness of segmentation for different seeds

3. Experiment

In order to show the effectiveness of the proposed method, we preform evaluational experiments.

Firstly, we evaluate the influence of difference of seeds on segmentation result. We show results of some initial seeds in Fig. 4. In Fig. 4, red color pixels are seed provided by a user. As parameters of this experiment, the number of colors in median-cut is 128, K of GMM is 5, the number of regions by watershed algorithm is 1000, θ of edge cost in proposed graph is 2000, λ = 200, threshold of extended neighborhood is 100. The size of test image in Fig. 4 is 260×195 pixels. From these results, sufficient foreground object is obtained by image segmentation. On the other hand, to evaluate the execution time, we implemented our proposed method with the support of the Intel OpenCV library 2.3 using a PC with Microsoft Windows XP. The hardware platform for the experiment was a PC equipped with an Intel Core i5 2.40 GHz CPU with 4 GB RAM. The average execution time is 468 ms.

Secondly, we evaluate of segmentation results by using various type of images. Examples of segmentation result are shown in Fig. 5. From these results. We confirmed the effectiveness of the proposed method.

4. Conclusion

In this paper, we proposed novel interactive image segmentation method based on visual saliency. Foreground likelihood and background likelihood are calculated from optimized GMM parameters and visual saliency based on provided seed pixels, respectively. Then, image segmentation is performed by optimizing proposed graph by using the graph-cut algorithm. In addition, in order to achieve an efficient segmentation, concept of neighborhood is extended to long-range neighborhood. As a result, various experiments showed that our method is effective, fast and easy for users.

Acknowledgments

This research was supported by JSPS, Grant-in-Aid for Scientific Research (Grant-in-Aid for Scientific Research (C)), JAPAN.

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Fig. 5 Examples of segmentation results by proposed method