Automatic Labelling of Seeds Based on Saliency Detection and Edge Detection for Image Segmentation

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***Abstract*— In computer vision, image segmentation transforms an input image into a more meaningful form which is easier to analyze. It can be used in the applications such as medical imaging, object detection, face recognition, etc. Generally, image segmentation can be distinguished as supervised and unsupervised categories. The result of supervised image segmentation is greatly affected by a user. Therefore, we propose an unsupervised method of image segmentation. We use saliency detection to label some informative and significant parts of the image, and then, we apply edge detection to label some details of the image and use the labelled image for image segmentation by Kim's method. In this way, we can automatically label the seeds to get the scribble and then segment the image into the foreground and the background. The simulation results show that our method is feasible for image segmentation.**

Keywords- segmentation;supervised segmentation; unsupervised segmentation; saliency detecion; edge detection.

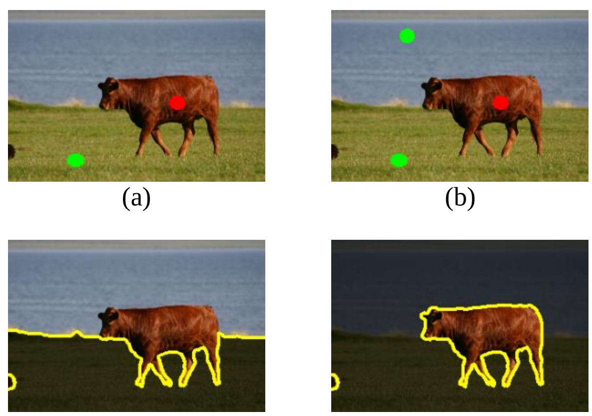
I. INTRODUCTION

In computer vision, image segmentation is the process of partitioning an image into several segments. The goal of image segmentation is to transform the input image into a more meaningful form which is easier to analyze. How to detect the objects which humans can recognize in the image is a big issue in image segmentation. Generally, image segmentation can be distinguished as supervised and unsupervised methods.

Supervised image segmentation [1]-[3] needs the user to label some seeds as scribbles. However, the result is greatly affected by the user. The result of segmentation image is shown in Figure 1 while using different scribbles in the Kim's algorithm [3]. Besides, supervised image segmentation is hard to evaluate the interactive time. Therefore, we propose an unsupervised method of image segmentation, which can't be affected by users.

Because the supervised image segmentation methods have some above-mentioned drawbacks. Thus, our motivation is to improve the supervised method's disadvantage and make our result of the unsupervised method close to that of the supervised method. Our goal is to transform the supervised method to the unsupervised method. We use saliency detection [7] and edge detection [8] to automatically label the seeds to get the scribble, and then we apply Kim's method to segment the image into the foreground and the background.

Recently, there are a lot of saliency detection method [4]-[7]. Moreover, we also apply Canny edge detection [8] to detect the edge because the method is simple and efficient. By saliency detection [7] and edge detection [8], we can automatically label seeds for image segmentation. Finally, we apply our scribble image with Kim's method [3] to get the final segmentation result. We will compare our method with Kim's method (supervised method) and the method of Donoser et. al [10] which is also unsupervised and based on saliency. The results show that our approach is good for image segmentation. In the section 2, we will briefly discuss some related works. In section 3, we will address our proposed algorithm. In section 4, we will show some experiment results and finally, we give our conclusion.



(a) (b) (c) (d)

Figure 1. The result of segmentation image while using different scribbles in the Kim's algorithm. (a) (b) The different scribbles labeled by different users. (c) The result of (a). (d) The result of (b)

II. RELATED WORKS

Image segmentation can be categorized into many categories: thresholding methods, clustering methods, region-based methods, edge-based methods, etc. The thresholding methods is the simplest method of image segmentation. The input image is transformed into a gray-scale image, and then segmented by a threshold value to get a binary image [11]. The main concept of clustering [12],[13] is to determine which components of a data set naturally "belong together". The region-based methods are widely used as well [14], [15]. Because segmentation consists on partitioning an image into a set of connected regions, we can find homogeneous regions according to a specific criterion (intensity value, texture). In addition, segmentation can also be done by edge detection techniques [8]. Donoser et al. [10] proposed another method which is unsupervised and based on saliency. The method automatically find salient regions first, and then focus on one different salient part of the image each time; the method finally, merge all obtained results into a composite segmentation.

We will compare the result of our method with that of Donoser et al. [10] because it is unsupervised and based on saliency as well. Furthermore, we will also compare the result of our method with the result of Kim's method (supervised method) [3]. According to the results, it shows that our result is good and very close to the result of Kim's method.

III. PROPOSED METHOD

The main idea of our method is labeling the seeds automatically and efficiently. To reduce the user's influence, we use our method to get the scribble of the image. The scribble provides the seeds to the method of nonparametric higher-order learning for segmentation [3].

First, given an input image, we detect the saliency of the image by Yang's method [7]. After saliency detection, we can automatically label the seeds. It contains three steps:

1. The foreground seeds and the background seeds by the foreground and the background threshold finding.
2. Locate the background seeds with four side examination.
3. Combine the seeds from step 1 and step 2 with the seeds generated by edge and saliency detection.

By these three steps, we can automatically and efficiently label the seeds to get a scribble image.

In the step of FG/BG threshold finding, we calculate the number of each saliency value and get the histogram of pixel's saliency value. We find that the background region is at least occupy 1/b area of an image, where b is a parameter (i.e., the lowest n_l saliency pixels of an image). Thus, we can get a proper background threshold (B_T) as

$$\sum_{sv=0}^{B_T} \mathrm{Num}(sv) \geq \mathrm{n}_l = \frac{N}{b}, \qquad (1)$$

where N is total number of pixels in the image, sv is saliency value (sv = 0,1,2, ..., 255), Num(sv): the number of pixels whose saliency value is sv.

Similarly, we find that the foreground region is at least occupy 1/f area of an image, where f is a parameter (i.e., the highest n_h saliency pixels of an image). Thus, we can get a proper foreground threshold (F_T) as

$$\sum_{sv=0}^{F_T} \mathrm{Num}(255 - sv) \geq \mathrm{n}_h = \frac{N}{f}, \quad (2)$$

where N is total number of pixels in the image, sv is saliency value (sv = 0,1,2, ⋯, 255), Num(sv): the number of pixels whose saliency value is sv.

Then, we label the FG/BG and remain some undetermined parts. For each pixel x_i, and its saliency value $S(x_i)$, if $S(x_i)$ is larger than F_T or is equal to F_T, label it as the foreground pixels (red). If $S(x_i)$ is smaller than B_T or is equal to B_T, label it as the background pixels (green). If $S(x_i)$ is larger than B_T but smaller than F_T, do nothing (undetermined). Thus, we can get 3 parts, the foreground, the background and the undetermined.

In addition to find proper the foreground/background thresholds, we also examine four sides of the image. By step 1, we've already known where the foreground is approximately located. We want to check the left, right, top, bottom regions, shown in Figure 2 and then label some background seeds.

We locate 4 regions $r_{s(l)}$, $r_{s(r)}, r_{s(t)}, r_{s(b)}$ and their corresponding borders are $b_{(l)}$, $b_{(r)}, b_{(t)}, b_{(b)}$, respectively. We use a size parameter s to define four regions $r_{s(r)}$, $r_{s(l)}, r_{s(t)}, r_{s(b)}$ as following.

$$r_{s(l)} = \{(x, y) | 1 \leq x \leq \frac{w}{s},\ 1 \leq y \leq h\}$$

$$r_{s(r)} = \{(x, y) | \frac{w(s-1)}{s} \leq x \leq w,\ 1 \leq y \leq h\}$$

$$r_{s(t)} = \{(x, y) | 1 \leq x \leq w,\ 1 \leq y \leq \frac{h}{s}\}$$

$$r_{s(b)} = \{(x, y) | 1 \leq x \leq w, \frac{h(s-1)}{s} \leq y \leq h\}$$

We define their corresponding borders $b_{(l)}$, $b_{(r)}, b_{(t)}, b_{(b)}$ as following:

$$b_{(l)} = \{(x, y) | 1 = x,\ 1 \leq y \leq h\}, \qquad (3)$$

$$b_{(r)} = \{(x, y) | x = w,\ 1 \leq y \leq h\}, \qquad (4)$$

$$b_{(t)} = \{(x, y) | 1 \leq x \leq w,\ 1 = y\}, \qquad (5)$$

$$b_{(b)} = \{(x, y) | 1 \leq x \leq w, y = h\}. \qquad (6)$$

The definition of 4 regions and their corresponding borders is shown in Figure 2. The left region and left border are shown and other regions can be shown similarly. Then, we examine four sides, respectively. We take left 1/s region $r_{s(l)}$ as an example. If there are foreground seeds in $r_{s(l)}$, retain the original edge. If there are no foreground seeds in $r_{s(l)}$, label the background seeds to the left boundary $b_{(l)}$, which is that region corresponding edge. Similarly, we examine the other three regions $r_{s(r)}, r_{s(t)}$, $r_{s(b)}$.

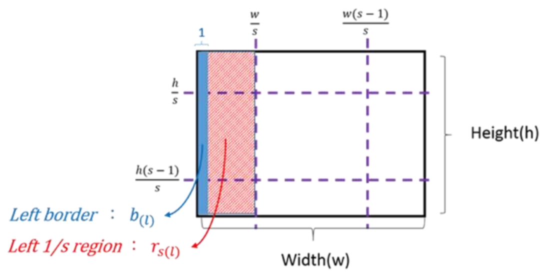


Figure 2.The definition of 4 regions and their corresponding borders.

After four sides examination, the extracted foreground still has some details which need to be improved. Thus, we apply Canny edge detection [8] to improve the segmentation. We find that the pixel in the edge image always belongs to the background in the saliency image. The green area is the background and the red area is the foreground. We use $(F_T - B_T)$/t to determine whether label the edge or not, where t is a parameter. The decision rule is as following：

For each pixel x_i in the edge image by Canny edge detection and its neighboring pixel$x_{i'}$. S(x_i) is the saliency value of pixel x_i, and S($x_{i'}$) is the saliency value of pixel $x_{i'}$.

if S($x_{i'}$)−S(x_i) is larger than $(F_T - B_T)$/t or S($x_{i'}$)−S(x_i) is equal to $(F_T - B_T)$/t, $x_{i'}$ is labelled *as* the foreground seed and x_i is labelled *as* the background seed; otherwise, do nothing.

After automatically seeds labelling, we carry out the method of nonparametric higher-order learning for segmentation [3].

IV. EXPERIMENT RESULTS AND ANALYSIS

We use our method to label the seeds efficiently and automatically. We compare with the method of nonparametric higher-order learning for interactive segmentation [3], which is greatly affected by users. The results of our method are very close to the results of nonparametric higher-order learning for interactive segmentation [3]. In addition, we also compare our method with the method [10], which also segment the image based on saliency. The parameters in our proposed method are presented in Table 1. Figure 3 and Figure 4 show the segmentation results of the image. We compare the result of our method with the result of Kim's method (supervised method) [3] first. According to Figure 3, it shows that our result is good and very close to the result of Kim's method (supervised method), which is a greatly affected by the users, while our method is unaffected by the users. Besides, we also compare the result of our method with the result of the method of Donoser et. al. [10]. According to Figure 4, the result of our method is better than that of the method [10], which is also an unsupervised segmentation method based on saliency because our method can label 2 bulls (foreground) only, but without the line between the grass and the lake.

V. CONCLUSION

In this paper, we proposed an unsupervised method based on saliency detection and edge detection to automatically and efficiently label the seeds. It is convenient because it can segment the foreground and background automatically and it doesn't need user interaction, which is quite important to segment a large data base of images.

References

[1] L. Grady, "Random walks for image segmentation," IEEE Transactions on Pattern Analysis and Machine Intelligence, 28(11):1768–1783, 2006.

[2] P. Kohli, L. Ladicky, and P. H. S. Torr," Robust higher order potentials for enforcing label consistency," Int J Computer Vision , 82:302–324, 2009.

[3] T.H. Kim, K.M. Lee, S.U. Lee, "Nonparametric higher-order learning for interactive segmentation," in: Computer Vision and Pattern Recognition (CVPR), 2010.

[4] H. Jiang, J. Wang, Z. Yuan, T. Liu, and N. Zheng," Automatic salient object segmentation based on context and shape prior," In British Machine Vision Conference, , 2011, pages 110.1–110.12 .

[5] Stas Goferman, Lihi Zelnik-Manor, and Ayellet Tal," Context-aware saliency detection," In CVPR, 2010, pages 2376–2383.

[6] K. Y. Chang, T. L. Liu, H. T. Chen, and S. H. Lai, "Fusing Generic Objectness and Visual Saliency for Salient Object Detection," in IEEE International Conference on Computer Vision, 2011, pp. 914-921.

[7] C. Yang, L. Zhang, H. Lu, X. Ruan, and M.-H. Yang, "Saliency detection via graph-based manifold ranking," In CVPR, 2013.

[8] Canny, J., A. "A Computational Approach To Edge Detection" IEEE Transactions on pattern analysis and machine intelligence, 1986, VOL. PAMI-8, NO. 6, Page 679 – 698.

[9] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Süsstrunk, "Slic superpixels," 2010, EPFL Technical Report no. 149300.

[10] M. Donoser, M. Urschler, M. Hirzer, and H. Bishof, "Saliency driven total variational segmentation," in Proc. of the IEEE Int'l Conf. Computer Vision (ICCV'09), 2009.

[11] Baradez, M.O., McGuckin, C.P., Forraz, N., Pettengell, R., Hoppe, A.: 'Robust and automated unimodal histogram thresholding and potential applications," Pattern Recognit., 2004, 37, (6), pp. 1131–1148

[12] A. K. Jain and R. C. Dubes, Algorithms for Clustering Data. Prentice Hall, 1988..

[13] F. Kurugollu, B. Sankur, and A. Harmanci, "Color image segmentation using histogram multithresholding and fusion," Image and Vison Computing," 2001, 19(13):915–928.

[14] Y. Deng, B. S. Manjunath, "Unsupervised segmentation of color-texture regions," IEEE Trans. on Pattern Analysis and Machine Intelligence, 2001, 23(8):800~810.

[15] Y. Deng, C. Kenney, M. S. Moore , B. S. Manjunath, "Peer group filtering and perceptual color image quantization," In: Proc. of the IEEE Int'l Symp. on Circuits and Systems, 1999. 21~24.

FG/BG threshold finding	b=3 f=100
Four sides examination	s=8
Combine edge/saliency detection	σ (Standard Deviation)：3 double threshold：0.1 and 0.2 t=3

Table 1. The parameters in our proposed method.

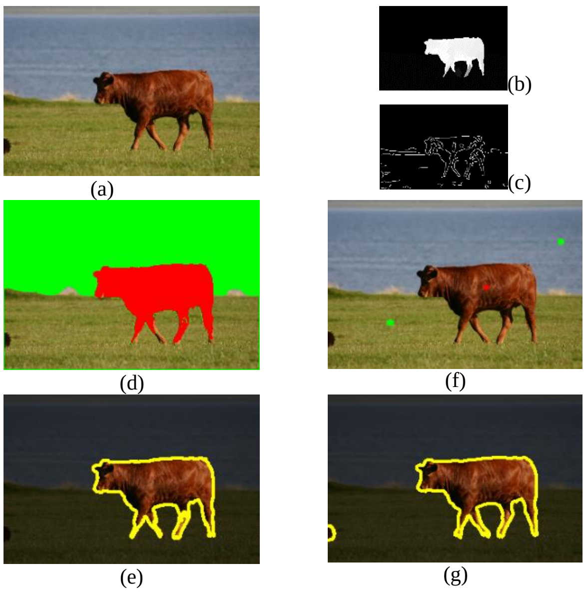


Figure 3. Segmentation result of the image. (a) Input image. (b) Result of saliency detection. (c) Result of edge detection. (d) Our scribble. (e) Our result. (f) Kim's scribble. (g) Kim's result.

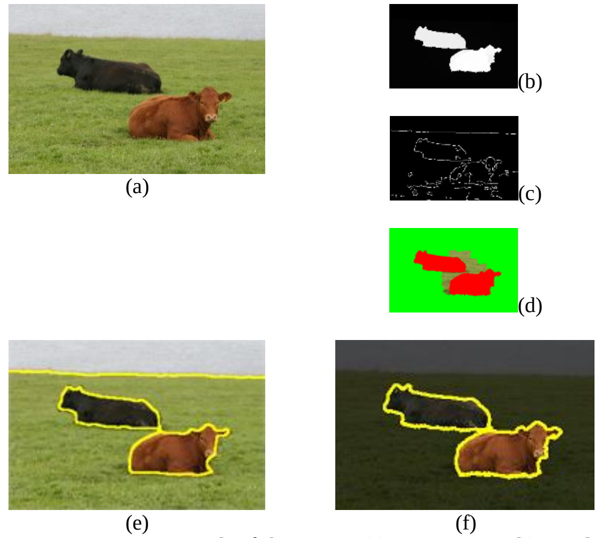


Figure 4. Segmentation result of the image. (a) Input image. (b) Result of saliency detection. (c) Result of edge detection. (d) Our scribble. (e) the result of Donoser et al. [10] (f) Our result.

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