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Automatic Segmentation of Object Region Using Graph Cuts Based on Saliency Maps and AdaBoost

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***Abstract*—In conventional methods for region segmentation of objects, the best segmentation results have been obtained by semi-automatic or interactive methods that require a small amount of user input. In this study, we propose a new technique for automatically obtaining segmentation of a flower region by using visual attention (saliency maps) as the prior probability in Graph Cuts. First, AdaBoost determines an approximate flower location using a rectangular window in order to learn the object and background color information using two Gaussian mixture models. We then extract visual attention using saliency maps of the image, and used them as a prior probability of the object model (spatial information). Bayes' theorem gives a posterior probability using the prior probability and the likelihood from GMMs, and the posterior probability is used as t-link cost in Graph Cuts, where no manual labeling of image regions is required. The effectiveness of our approach is confirmed by experiments of region segmentation on flower images.**

I. Introduction

Extracting the foreground objects in static images is one of the most fundamental tasks in image content analysis, object detection and image editing. The task can be formulated as an image segmentation problem.

In recent years, the image segmentation problem has been formalized as an optimal solution problem. The graph cuts technique proposed by Boykov [1] provides a globally optimal solution for segmentation, where it is able to compute the global minimum solution, and the cost function is general enough to include both region and boundary properties of the segments. However, it requires the user to guide the segmentation by manually segmenting image region (e.g. [2], [3]). To deal with this problem, an automatic segmentation algorithm based on AdaBoost learning and iterative Graph-Cuts has been shown in [4], where AdaBoost is used to automatically find the approximate location of the object using a trained classifier, and the iterative Graph-Cuts method then is used to model the automatic segmentation problem.

In this paper, in order to deal with automatic segmentation of image regions, a model of saliency-based visual attention [5] is integrated with Graph Cuts since some object regions appear to increase visual attention more than backgound regions. Therefore, we may use the saliency map as a prior probability of the object model (spatial information). First, AdaBoost determines an approximate flower location using a rectangular window to learn the object and background color information using two GMMs, and Bayes' theorem then gives a posterior probability using the prior probability. The posterior probability is used as t-link cost in Graph Cuts, where no manual labeling of image regions is required.

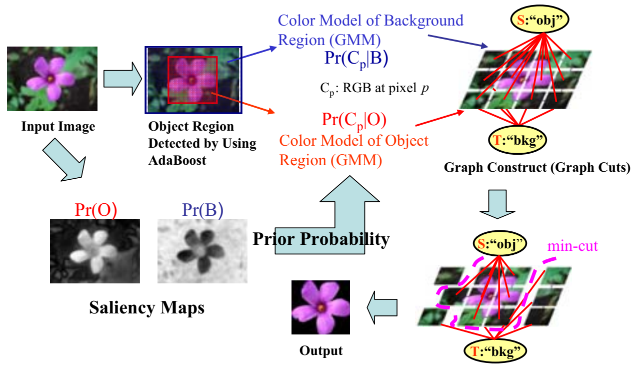

Fig. 1. Automatic Segmentation Using Graph Cuts Based on Saliency Maps and AdaBoost

II. Automatic Segmentation Using Graph Cuts Based on Saliency Maps and AdaBoost

A. *Overview of the Proposed Method*

An overview of our automatic segmentation technique is given in Fig. 1. First, an approximate flower location is estimated using AdaBoost to provide the data for the initial object color model, where classifiers are trained using a flower image database. The detected rectangular region of an object flower is required to train the object (and background) color information using a Gaussian mixture model, and then the likelihoods of $\Pr(C_p|O)$ and $\Pr(C_p|B)$ are computed, given two trained GMMs (Object and Background models).

A saliency map, which represents visual attention, is computed by [5], and it is used to provide a prior probability of object model ($\Pr(O)$) in this paper because an object flower region may have high saliency, compared with a background region. The next stage of the algorithm is to compute a posterior probability using the prior probability and the likelihood from a GMM.

$$\Pr(O|C_p) = \Pr(O)\Pr(C_p|O)/\Pr(C_p) \quad (1)$$

$$\Pr(B|C_p) = \Pr(B)\Pr(C_p|B)/\Pr(C_p) \quad (2)$$

Here, C_p is a vector in color space (RGB) at pixel p. Since the denominator $\Pr(C_p)$ is not dependent on the comparison of the above two posterior probabilities, it can be disregarded in Eq. (1) and (2). The obtained posterior probabilities are used to determine the cost of each edge in Graph Cuts. Finally, automatic object segmentation is performed iteratively by using the min-cut/max-flow algorithm.

B. Estimation of a Prior Probability of the Object Using a Saliency Map

We extract visual attention by using saliency maps in the image [5], and the saliency is used as a prior probability of the object model in Graph Cuts in order to deal with automatic segmentation of image regions. The first step of the algorithm is to downsample an input image using Gaussian pyramids from 1:1 (scale zero) to 1:256 (scale eight), where 9 scale images are created at scale $c \in \{0, ..., 8\}$. Each feature is then computed by a set of linear center-surround operations akin to visual receptive fields, where it is implemented as the difference between fine and coarse scales. The obtained feature maps are combined into three maps, $\bar{I}$ for intensity, $\bar{C}$ for color, and $\bar{O}$ for orientation. Finally, the saliency map is obtained by combining the three maps linearly.

In this paper, the saliency value at each pixel is used as a prior probability of the object model in order to deal with the spatial information of the object as follows:

$$\Pr(O) = x_p, \qquad \Pr(B) = 1 - \Pr(O) \tag{3}$$

where the saliency value at each pixel, x_p, is normalized into a range of 0 and 1.

C. Region Segmentation Using Graph Cuts

Graph Cuts in [1] computes a globally-optimal binary segmentation minimizing the following energy function (segmentation score).

$$E = \lambda \textstyle\sum_{p \in P} R_p(A_p) + \sum_{(p,q) \in N; A_p \neq A_p} B_{p,q} \tag{4}$$

Here, N is the set of neighboring pixels, $B_{p,q}$ denotes the boundary properties, and A_p specifies the assignment to pixel p. In conventional methods, the regional term $R_p(A_p)$ is obtained using histograms (or GMMs) for "object" and "background" intensity distributions: $\Pr(C_p|O)$ and $\Pr(C_p|B)$, where a user is required to enter a few "object" and "background" seeds [1], or AdaBoost determines an approximate flower location using a rectangular window [4]. On the other hand, our approach uses the posterior probabilities in Eq. (1) and (2), where the prior probability provides spatial information of the object using a saliency map.

III. Segmentation Experiments on Flower Images

We used 150 flower images in the experiments and evaluated our approach with an error rate as follows: Err [%] = (E_O/P + E_B/P)$\times$ 100, where E_O and E_B are the number of error detection pixels in the object and the background regions, respectively. The total number of pixels in a whole image is given by P.

Fig. 2 (a) shows that the conventional method (Graph Cuts using AdaBoost) [4] results in a higher error rate, compared

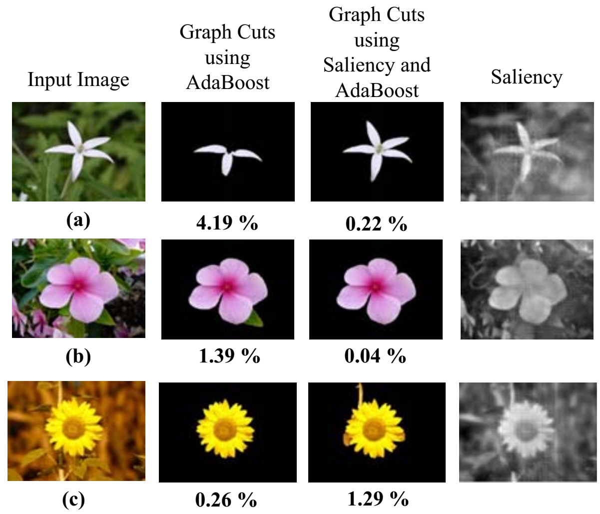

Fig. 2. Segmentation Results and Error Rate for each flower

to our result, because [4] uses the detected rectangular region of the object flower to train the color information of the object, where the rectangular region includes a proportionally large of amount of the background region compared to the object, which makes up a small proportion of the enclosed area. On the other hand, as shown in Fig. 2 (a) and (b), our method achieves better performance since our method can obtain spatial information of the object from the prior probability that is computed using the saliency map. In Fig. 2 (c), however, our technique shows a higher error rate because the wrong saliency was obtained for the high contrast region. For 150 flower images, the average error rates of our approach and [4] were 2.16% and 3.53%, respectively.

IV. Conclusion

This paper has described an automatic segmentation of image regions. In this paper, we extract visual attention by using saliency maps of the image and use the saliency as a prior probability of the object model in Graph Cuts to deal with the spatial information of the object. The experiment results on flower segmentation indicate that our method offers considerable advantages for automatic object segmentation.

References

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