

INTERACTIVE IMAGE SEGMENTATION WITH SEED PROPAGATION

Korupolu Narasimha Murthy¹, Karumuri Raja Sekhar²

¹Student, UCEK, JNTUK, KAKINADA

²Assistant Professor, UCEK, JNTUK, KAKINADA

Abstract - Image segmentation aims to separate the desired foreground object from the background. Since color in natural images are very complex, automatic segmentation of foreground objects from the complex background meets a significant obstacle when foreground and background have similar features. To avoid this problem, Interactive image segmentation helps by taking the advantage of user's interactive input. In interactive image segmentation, the interactive inputs provided by users play an important role in guiding image segmentation. But, the simple inputs often cause bias which leads to failure of preserving of object boundaries. To effectively use the limited interactive information, an adaptive constraint propagation (ACP) is employed for semi supervised kernel matrix learning (SS-KML) which adaptively propagates the interactive information into the whole image by keeping the original data coherence. Adaptive constraint propagation (ACP) cut using seed propagation can achieve the discriminative structure learning and reduce computational complexity. Discriminative structure learning is similar to problem formulation, which optimizes adaptive constraints together with global smoothness in learning a discriminative structure kernel mapping

Key Words: Adaptive constraint propagation (ACP), seed propagation, interactive image segmentation.

1. INTRODUCTION

Interactive image segmentation is a promising way to provide users with satisfactory foreground object extraction by using user interaction in image segmentation. Gaussian mixture Markov random field [10] constructed a generative probabilistic model with user interactions for foreground and background inference. Decision tree field [7] treated the foreground/background segmentation as a random forest based inference where the tree structure is learned by a two-step heuristic. Both Markov random field methods required a learning procedure on a set of given training images, thus the ability of the trained classifier can vary greatly depending on the training images. Moreover, a lot of elaborate methods have been developed to improve convenience and efficiency in interactive image segmentation. Interactive graph cuts [4] were presented employing *Graph Cut* to extract global optimal separation of foreground/background and provide a balance of boundaries. Geodesic star convexity [11] introduced star-convexity constraints on interactive graph cuts [4] to improve the connectivity of segmented foreground objects.

Grab Cut improved interactive graph cuts with the number of interactions (in the form of drawing rectangles around desired foreground objects) reduced significantly. [12] presented a prior bounding box to *Grab Cut* to improve the tightness of segmented foreground objects to the given rectangular-box. Hierarchical graph cuts [13] extended *Grab Cut* with coarse-to-fine object extraction and boundary refinement. *Lazy Snapping* [14] also adopted a coarse-to-fine strategy by specifying foreground/background with line markers and boundary refinement.

2. ACP CUT

Most of the previous work has used interactive markers locally [5], [6], [14], thus leading to bias in segmentation. However, in *ACP Cut*, we learn a global discriminative kernel matrix using interactive markers and a global data structure obtained by graph Laplacian to avoid bias. The bias from constraints to the data structure is alleviated by adaptive constraints because we perform kernel learning by optimizing both data smoothness and adaptive constraints.

ACP Cut combines the user's interactive information with SS-KML to learn a global discriminative structure for foreground/background segmentation, thus achieving the state-of-the-art performance in interactive image segmentation.

Adaptive constraints in *ACP Cut* adaptively propagate characteristics of the user's interactive information through the whole image and effectively preserve global discriminative data coherence, thus avoiding bias caused by the limited interactive information.

Seed propagation in *ACP Cut* significantly reduces the computational complexity in interactive image segmentation by decomposing the learning procedure in an image into blocks.

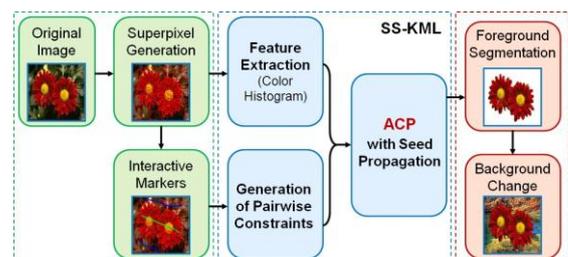


Fig.1. Block diagram of ACP Cut. In the block of Interactive Markers, green lines are foreground markers while blue

lines are background ones. ACP: adaptive constraint propagation, SS-KML: semi-supervised kernel matrix learning.

A. Feature Extraction and Constraints Generation

The number of superpixels given by mean-shift segmentation is mainly determined by a limited number of pixels m in a superpixel, i.e., a superpixel which contains less than m pixels is merged into its neighborhood. Then the number of superpixels given by mean-shift segmentation is mainly determined by a limited number of pixels m in a superpixel, i.e., a superpixel which contains less than m pixels is merged into its neighborhood.

That is, each color channel of RGB is quantized uniformly into 4 bins, and then the color histogram of each superpixel is represented in 4096 dimensionality ($2^4 \cdot 2^4 \cdot 2^4 = 4096$). The color histogram is normalized by the pixel size in a superpixel. Given an image of n

$$w_{ij} = \sum_{u=1}^Z \sqrt{H_i(u) \cdot H_j(u)}$$

On the contrary, if two superpixels have different markers, then they belong to the cannot-link constraints C . Once M and C are created, the global image discriminative structure can be learned over the entire set of superpixels and pairwise constraints for image segmentation as Section II-B.

B. Discriminative Structure Learning

The data distributions are embedded and reshaped according to the pairwise assumption that two must-link superpixels become close while two cannot-link ones become far apart, as well as the global smoothness assumption that superpixels similar to two must-link ones become close while superpixels similar to two cannot-link ones become far apart. Global image discriminative structure learning in ACP Cut similar to the problem formulation in [20].

C. Segmentation

The global k-means algorithm [23] is performed for foreground object extraction to assign a label of foreground/background to each superpixel of an image over the learned discriminative structure by considering the columns of the kernel matrix as learned discriminative features of superpixels. Detailed descriptions of ACP Cut are given in Algorithm 2. In the segmentation results, ACP Cut may assign some background superpixels as foreground, or foreground may be missing some from the background. This is caused by superpixels sharing similar characteristics in both foreground and background. Since segmented regions generally

have closed boundaries. The foreground regions without foreground markers are merged into background, while the background regions involved in foreground objects are merged into foreground.

3. SEED PROPAGATION

1) The would like to perform the discriminative kernel learning (2) in manner of sub-matrices by learning a small sized seed matrix on foreground/background seeds and then deriving the other block matrices associated with unconstrained superpixels based on the learned seed matrix. Partition Φ into two sub-matrices Φ_1 and Φ_u corresponding to foreground/ follows: background seeds and unconstrained superpixels, respectively, as

4. RESULTS

To verify the superiority of Seed Propagation, we perform experiments on natural images and the Berkeley segmentation database. The performance is evaluated in both effectiveness and efficiency by true positive rate (TPR), true negative rate (TNR), global foreground and background accuracy (ACC) and runtime of learning algorithms. All experiments are conducted on a PC with Intel (R) Core(TM) i3 CPU (3.20 GHz) and 3.05G RAM running a Windows 10 environment and MATLAB R2018a.

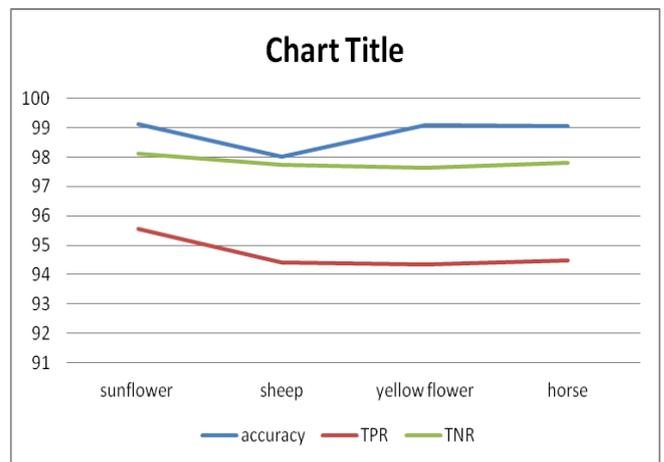


Chart 1:Quantative measurements

The measurements are accuracy, TPR, TNR values for Sunflower, Sheep, Yellow flower and horse are shown in above graph by plotting different colors. The Highest value for the Accuracy is nearly equal to 99. The TPR value is 98 and the TNR value is 95.5.



TABLE: Quantitative Evaluation Results interms of Accuracy, TPR,TNR

	accuracy	TPR	TNR
sunflower	99.13	95.56	98.13
sheep	98.02	94.42	97.75
yellow flower	99.08	94.36	97.65
horse	99.06	94.48	97.82

5. CONCLUSION

In this paper *ACP Cut* based on adaptive constraints and seed propagation to learn a global image discriminative structure for interactive image segmentation. Adaptive constraints adaptively propagate characteristics of the user's interactive information into the whole image while preserving the original data coherence, thus avoiding bias caused by the limited interactive information which distorts the global image discriminative structure. Seed propagation in *ACP Cut* recursively learns the discriminative structure and greatly reduces the computational complexity. Experimental results and their corresponding evaluations indicate that *ACP Cut* outperforms the other methods for interactive image segmentation in terms of both effectiveness and efficiency.

REFERENCES

- [1] C. Jung, M. Jian, J. Liu, L. Jiao, and Y. Shen, "Interactive image segmentation via kernel propagation," *Pattern Recognition*, vol. 47, no. 8, pp. 2745–2755, 2014.
- [2] M. Jian, C. Jung, Y. Shen, L. Jiao, and J. Liu, "Adaptive constraint propagation for semi-supervised kernel matrix learning," *Neural Processing Letters*, 2014.
- [3] D. Comaniciu and P. Meer, "Mean shift: a robust approach toward feature space analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 5, pp. 603–619, 2002.
- [4] D. Comaniciu, V. Ramesh, and P. Meer, "Kernel-based object tracking," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 5, pp. 564–577, 2003.
- [5] A. Likas, N. Vlassis, and J.J. Verbeek, "The global k-means clustering algorithm," *Pattern Recognition*, vol. 36, no. 2, pp. 451–461, 2003.
- [6] J. Ning, L. Zhang, D. Zhang, and C. Wu, "Interactive image segmentation by maximal similarity based region merging," *Pattern Recognition*, vol. 43, no. 2, pp. 445–456, 2010.
- [7] S. Nowozin, C. Rother, S. Bagon, T. Sharp, B. Yao, and P. Kohli, "Decision tree fields," *Proceedings of IEEE Conference on Computer Vision*, pp. 1668–1675, 2011.
- [8] B. Price, B. Morse, and S. Cohen, "Geodesic graph cut for interactive image segmentation," *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3161–3168, 2010.
- [9] T. Nguyen, J. Cai, J. Zhang, and J. Zheng, "Robust interactive image segmentation using convex active contours," *IEEE Transactions on Image Processing*, vol. 21, no. 8, pp. 3734–3743, 2012.
- [10] R. Carsten, K. Vladimir, and B. Andrew, "Grabcut: interactive foreground extraction using iterated graph cuts," *ACM Transactions on Graphics*, vol. 23, no. 3, pp. 309–314, 2004.