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A Study of Interactive Image Segmentation using Multiple Linear Reconstructions in Windows

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***Abstract*--An interactive image segmentation is employed here for classification of the image which is graph based transductive. Specifically,with an image, the color of each pixel in it is linearly reconstructed on par with those of the remaining pixels in this window. In order to reconstruct class labels linearly the corresponding optimal reconstruction weights will be kept unchanged The errors in the class labels are estimated in each window, To develop a learning model the errors are gathered.**

Then, the integration is performed over class information to regularize the framework about the user specified area of interest in the image (foreground and background pixels) Under this framework, a globally optimal labeling can be finally obtained. The complexity involved is analyzed, and an approach for speeding up the algorithm is surveyed. The experimental results are compared which illustrate s the validity of the algorithm.

Keywords: MLRW, Interactive Image Segmentation

I. INTRODUCTION

Image segmentation is basically a partitioning of the image grid into different regions such that the pixels in each region will share the same visual features. Although automatically segmenting natural images which was employed in the last few decades is a difficult task. The difficulties may be in the two levels on the low level, it is difficult to properly model the visual elements which includes colors, textures, and other Gestalt features in the image that needs to be segmented. On the high level, it is difficult to group the visual patterns into the required object regions. none of these two aspects of complexity can be solved unless the prior knowledge about the image. Such difficulties in general encourage the development of interactive image segmentation [3], [4], [10], [12], [17], [20], [25], [26]. With human intervention, the user can label the foreground and background area. Such a labeling in the pattern classification will reduce the complexity of pattern modeling as well as the pattern grouping. Some interactive image segmentation algorithms were developed in the past decade [3], [4], [10], [17], [5], [19], [20],[23]. Most of the earlier techniques such as intelligent scissors [12], [13], snapping [6], and jet-stream [15] demands the user to label the pixels near the area of the desired objects. Recently, the style of user interaction has been prominently improved. Within the interface of the system, the user can drag the mouse in order to scribe zig-zag lines on the foreground and background regions. Such an improvement of interaction is beneficial from the development of the region-based algorithms. Typical algorithms in this family include magic wand, intelligent paint [2], [16], sketch-based interaction [21], Graph Cut (GC) [3], [4], Grabcut [17], lazy snapping [10], random walks (RW) [8], image matting [5], [8], [19], [20], [23], [28], distance-based interaction [14], and so on. Taking the pixels covered by the zig-zag lines as training examples, the segmentation task can be naturally addressed as a problem of pattern classification. This provides the work setting for applying statistical inference or machine learning algorithms to interactive image segmentation [10], [17], [23], [7]. the complexity of pattern modeling as well as the ambiguity of pattern grouping. In the past decade, some interactive image segmentation algorithms have been developed [3], [4], [10], [17], [5], [19], [20], [23]. Most of the early techniques such as intelligent scissors [12], [13], snapping [6], and jet-stream [14] require the user to label the pixels near the boundary of the desired objects. For example, when using the intelligent scissors, the user should gaze at the region near the boundary. Labeling in this way is not an easy work. Recently, the style of user interaction has been significantly improved. Within the interface of the system, the user can drag the mouse to scribe zig-zag lines on the foreground and background regions. Such an improvement of interaction is beneficial from the development of the region-based algorithms. Typical algorithms in this family include magic wand, intelligent paint [2], [16], sketch-based interaction [21], Graph Cut (GC) [3], [4], Grabcut [17], lazy snapping [10], random walks (RW) [6], image matting [5], [8], [19], [20], [21], [28], distance-based interaction [15], and so on. Taking the pixels covered by the zig-zag lines as training examples, the segmentation task can be naturally addressed as a problem of pattern classification. This provides the work setting for applying statistical inference or machine learning algorithms to interactive image segmentation [10], [11], [23], [7]. is fundamentally important as it helps to reduce the complexity of pattern modeling as well as the ambiguity of pattern grouping. In the past decade, some interactive image segmentation algorithms have been developed [3], [4], [10], [17], [5], [19], [20], [23]. Most of the early techniques such as intelligent scissors [12], [13], snapping [6], and jet-stream [14] require the user to label the pixels near the boundary of the desired objects. For example, when using the intelligent scissors, the user should gaze at the region near the boundary. Labeling in this way is not an easy work. Recently, the style of user interaction has been significantly improved. Within the interface of the system, the user can drag the mouse to scribe zig-zag lines on the foreground and background regions. Such an improvement of interaction is beneficial from the development of the region-based algorithms. Typical algorithms in this family include magic wand, intelligent paint [1], [15], sketch-based interact-ion [21], Graph Cut (GC) [3], [4], Grabcut [17], lazy snapping [9], random walks (RW) [7], image matting [5], [8], [19], [20], [21], [28], distance-based interaction [15], and so on. Taking the pixels covered by the zig-zag lines as training examples, the segmentation task can be naturally addressed as a problem of pattern classification. This provides the work setting for applying statistical inference or machine learning algorithms to interactive image segmentation [10], [11], [23].

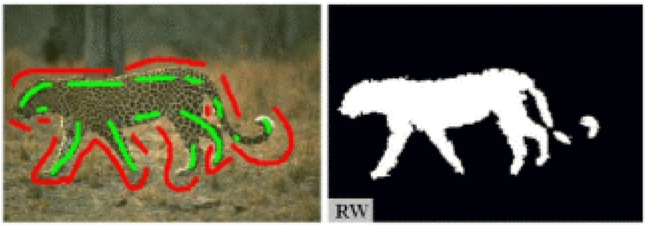

Fig 1: Left: the leopard image [10] with user specified strokes. Right: the segmentation obtained by RW. The tail is incorrectly segmented.

Inferring on Markov random field (MRF) constructed on the image grid is a fundamental approach to pixel labeling [8]. The optimization task can be solved via maxflow/mincut [2], [3], [9], [16] or belief propagation [22]. The algorithm is effective in most cases. However, if the foreground and background regions have similar colors, the gap of the likel-ihood costs in these regions will be decreased. This will degrade the quality of segmentation. Fig.1 gives an example. Here some background regions are incorrectly segmented. Recently, Gray proposed RW for interactive image segmentation [6]. In RW, each unlabeled pixel will be assigned the same label of the seed point (one of the user labeled pixels) that a random walker starting from this unlabeled pixel reaches first [6]. RW is fast and can provide satisfactory segmentation for most natural images. However, for complex natural image, it may generate unsatisfactory segmentation. Fig. 2 gives an example, where the tail of the leopard is incorrectly segmented. Thus, more user interactions are needed to improve the quality of segmentation. Algorithms based on discriminative learning have also been introduced into inter-active segmentation. Xiang et al. developed spline regression (SR) to directly map the pixel features to be class labels [25]. The spline is learned from the user-specified foreground and background pixels, and used as a prediction function for those unlabeled pixels. SR is fast and can generate satisfactory segmentation for most natural images with adequate user specified strokes. However, as it is a discriminative learning algorithm, the segmentation may include some noise. Fig. 3 illustrates an example. In machine learning, transductive learning [21] is an important inferring method. The goal of the learner in transductive learning is to infer the class labels of the remaining unlabeled data points. Thus, it is suit-able for the task of interactive image segmentation. In literature, Zhu et al. proposed an inferring approach with Gaussian random field (GRF) [29], and Zhou et al. developed an iterative framework of learning with local and global consist-ency (LLGC) [28]. These two algorithms are developed on the edge-weighted graph. Gaussian function are used to evaluate edge weights. However, the parameter of Gaussian function should be well tuned to data. Later, Xiang et al. proposed local spline regression (LSR) for semi-supervised learning [24]. In contrast, LSR does not contain parameters that should be well tuned to data. As one of its applications, LSR has been applied to interactive image segmentation [24]. But how to speed up LSR with unchanged segmentation accuracy is still a problem to be solved. This paper presents a graph-based algorithm for interactive image segmentation. Specifically, given a 3 3 local window, the color of each pixel in it will be linearly reconstructed with those of the remaining eight pixels. The optimal weights will be transferred to linearly reconstruct its class label (foreground/ background). This treatment is largely motivated from the manifold learning algorithm of locally linear embedding (LLE) [17]. 343 But beyond LLE where only one data point is reconstructed in each given data neighborhood, we will

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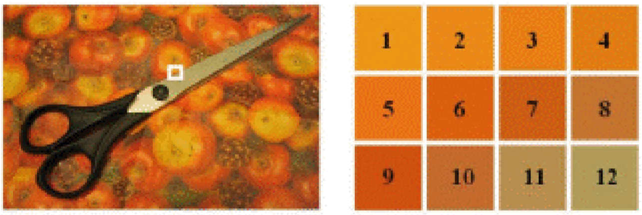
reconstruct all the pixels in each spatial window. In this process, the label reconstruction errors are estimated. Then, the information about the user-specified foreground and background is introduced into a regularization framework. The segmentation task is finally solved via global optimization. The main advantages or details of our algorithm can be highlighted as follows.

- Using the same user strokes, MLRW algorithm can generate more accurate segmentation on most complex natural images where graph cut and random walks do. Experiments also indicate that MLRW algorithm shows better adaptability to most natural images, compared with GRF and LLGC.
- Parameters used are all independent of data and need not be tuned well from image to image.
- The core computation can be easily implemented.



(a) (b)

Fig 2 (a) Scissors image [16] with 337 225 pixels. (b) Twelve pixels located in the scissors image in (a) with coordinates: (x; y) x [183; 186]; y [74; 76]

II. MLRW ALGORITHM

The steps of the algorithm, with multiple linear reconstructions in windows (MLRW), An image with 9x 9 and the 3x3 windows the size of image are overlapped with each other. Thus, for image with pixels, There is a need to allocate about nonzero stands for the integer not greater than the elements to fetch the matrix M

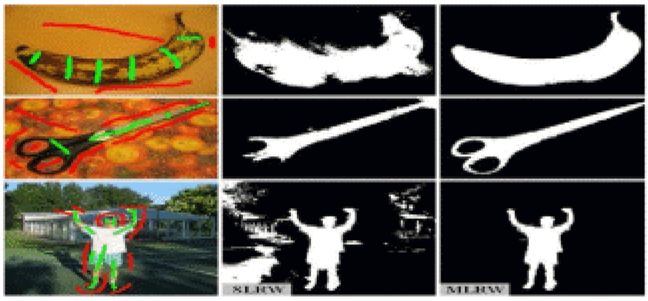


Fig 3.Left column: source images with the user specified strokes. Middle column: results obtained by SLRW with 5X5 windows. Right column: results obtained by our MLRW with 3X3 windows.

But the sparsity ratio will be approximately 99% Sparsity facilitates the storage and also helps to reduce the complexity involved in computation. Further the performance of the algorithm is analyzed . In Fig. 2, pixel "9" will be employed to reconstruct pixel "7". Note that pixel "9" is also in the 5x5 window with pixel "7" at the center. The performance of reconstructing, respectively, all of the pixels in 3x3 windows will not be equivalent to that of reconstructing only the center pixel in 5x5 windows. As for this point, In Fig.3 the left column illustrates the user-specified strokes. The middle column shows the segmentation results by only reconstructing the center pixels of 5x5 windows,using single linear reconstructions in windows (SLRW). The right column shows the results obtained by MLRW. With the large windows of image MLRW would give satisfactory results on par with SLRW.

III. COMPARISON

The comparison of MLRW with the commonly-used algorithms of graph cut (GC) [2], [3], [9] and RW [6] in interactive image segmentation is presented, and also compared it with the classical algorithms of GRF [29] and LLGC [28]. In addition, SLRW will be also compared to illustrate the effectiveness of this algorithm. The label likelihood of pixels are calculated via the lazy snapping approach . To speed up the calculation, K means clustering algorithm with 20 clusters is run to cluster, respectively, the colors of the user-specified foreground and background pixels as used in lazy snapping approach. The Berkeley database [10] and Grabcut database [16] are used to conduct the experiments. Figs. 9–12 are used to illustrate the results obtained by different algorithms. In each of the illustrated figure, the first and second columns are the source images and the user-specified strokes. From the third to the eighth column are the results that are obtained by different algorithms like GC, RW, GRF, LLGC, SLRW, and MLRW, respectively. The last column lists the ground truth for comparison.A comparative study is performed over the developed algorithms of SR [25], LSR [24], and MLRW

Fig. 4 illustrates the segmentation of the 20 images obtained, respectively. The user-specified strokes about the background and foreground are shown in Fig 4.

A better segmentation results may be expected out of Both LSR and MLRW compared with SR. The segmentation quality level may be of the same in both LSR and MLRW. The Segmentation results of the comparison done are seen in the Fig 5

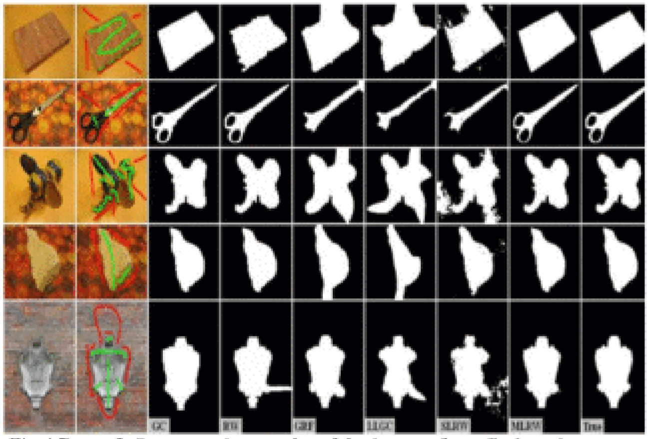


Fig 4 Demo I: Segmentation results of the images from Grabcut image database. The images are scaled for arrangement.

IV. Summary of the Comparison of SR LSR and MLRW

SR is developed in view of discriminative learning. That is, the features of the user-specified foreground and background pixels are employed to train a spline,which is used as a prediction function for those unlabeled pixels. SR need not solve a large group of linear equations. Thus, it is fast and can run with low memory. However, SR may generate segmentation with noises

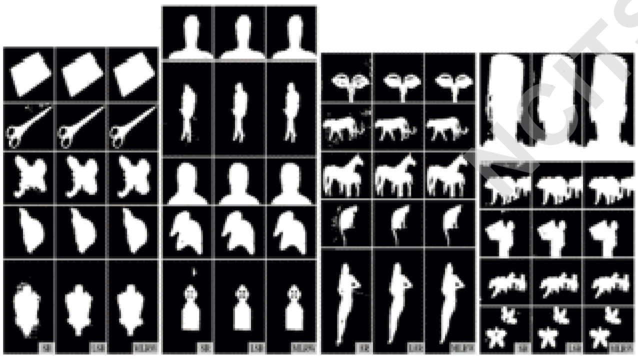


Fig 5 Segmentation results of the images obtained by SR, LSR, and MLRW, with the same user-specified strokes illustrated

V. CONCLUSION

A graph-based classification algorithm for interactive image segmentation which may be expected to provide a good result on par with other interactive image segmentation approaches.. It is developed with multiple linear reconstructions in image windows. The key idea is to linearly reconstruct the color vector of each pixel with those of the remaining pixels also in the same window. the class label of each pixel of the image are reconstructed linearly with the estimated optimal reconstruction weights. In this way, the label reconstruction errors are estimated and are also minimized to obtain the final segmentation results. The algorithm is analyzed over many types of natural images. A speeding up approach is presented. A comparative study between the developed algorithms are studied. Comparative experimental results illustrate the validity of the MLRW algorithm.

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