Using Multi-layer Random Walker for Image Segmentation

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***Abstract*—Image segmentation can be considered as a label decision problem which assign different labels to every pixel according to its features. In this paper, we propose a supervised and interactive image segmentation algorithm. In our approach, we construct a new graph model which consists of a super-pixel layer and a high order layer. The super-pixel layer is composed by over-segmentation regions called superpixels and the high-order layer is generated by combining edge detection and these over-segmentation regions. Then we construct a graph model and use a random walk algorithm to find the maximum probability label value for each superpixel. The proposed method shows very satisfactory results for some natural images.**

Keywords—Image segmentation; Random Walker, superpixels

I. INTRODUCTION

Image segmentation is very important issue in computer vision. It is often defined as the problem of partition image into many particular groups. There are many unsupervised segmentation algorithms including K-means clustering [6], mean shift [5], or Saliency detection [7]. The unsupervised segmentation does not need any user input. However, there are two difficulties of the segmentation in natural images. One difficulty is a weak boundary problem and the other is a texture problem. The unsupervised segmentation approaches would not do well in such two conditions in natural images. To segment natural images, many supervised approaches have been proposed in recent years. There are two types of supervised segmentation according to user inputs. The first one is based on object's boundary and the second ones is based on object's features. The supervised segmentation approach based on object's boundary such as the snake [10] and the intelligent scissor [11] needs a piece of boundary or closed boundary given by the user. The supervised approach based on features such as graph cut [8] needs the object's features labeled by the user. In this paper, we propose a new graph model to solve image segmentation problem by using the random walker algorithm with features of superpixels of the object in the image.

II. RELATED WORK

There are many supervised algorithms and we focus on supervised segmentation based on object's features. The Graph cut algorithm [8] is one of famous supervised segmentation and views image as a weighted graph model to reflect intensity changes. The user labels some nodes as the background and others as the object. Then the graph cut perform max-flow/min-cut analysis to find the minimum-weighted cut to show segmentation results. However, it also causes problems when the contrast is low or seed number is small. In order to avoid these problems, the random walker algorithm [9,13,14] has better performance than graph cut [8].

In the random walks algorithm, we treat an image as a graph model with a number of vertices and edges. Each node represents a pixel for an input image and each edge is assigned a real-value corresponding to the likelihood of the similarity between two pixels. The user marks some nodes based on object's feature which we want to partition. Those nodes are called seeds. Figure 1(a) shows our graph model before the random walks algorithm. The nodes L_1 、L_2 are different seeds labeled by the user. The yellow nodes in Figure 1(a) are not labeled by user and would determine label value by the random walker algorithm. We would get the solution expressed in term of the set of posterior probabilities for every nodes as in Figures 1 (b) and 1(c). Figure 1(b) shows the probability matrix that a random walker starting from each node reaches the seed L1. Figure 1(c) is the probability that the random walker starting from seed L2 reaches each node first. Figure 1(d) shows the segmentation by the probability result at the steady state by the random walker algorithm.

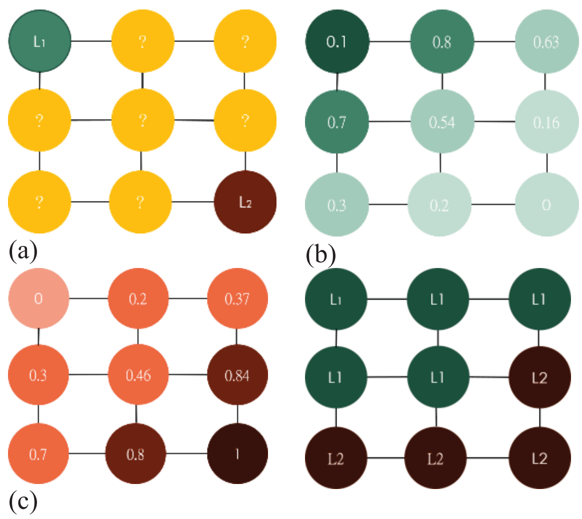


Figure 1: The steps of the random walks algorithm (a) Seed points with segmentation, (b) Probability that a random walker starting from seed L1 reaches each node, (c) Probability that a random walker starting from seed L2 reaches each node, (d) Labeled nodes after the random walker algorithm.

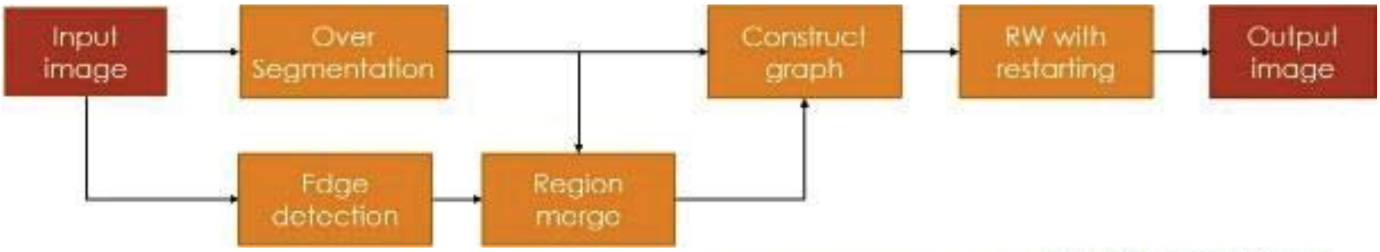


Figure 2: The proposed graph model for image segmentation

III. The Proposed method

Figure 2 shows our proposed method for image segmentation. Our algorithm has four steps including a super-pixel layer, a high-order layer, a graph construction model and a random walks algorithm. The super-pixel layer consists of over segmentation of the input image. We use an over-segmentation algorithm [3] to group pixels which have similar features from the input image. The output of over-segmentation algorithm is called the super-pixel layer in our method. The high-order layer is done by an edge detection method and do regions merge for superpixels. The next step is to construct the graph model by the edge weight and an adjacency matrix between the super-pixel layer and the high-order layer. Finally, we execute the random walker algorithm [1] to solve image segmentation problem. The random walker algorithm uses a linear system method to compute the probability of a superpixel which belongs to the foreground or the background for every superpixel.

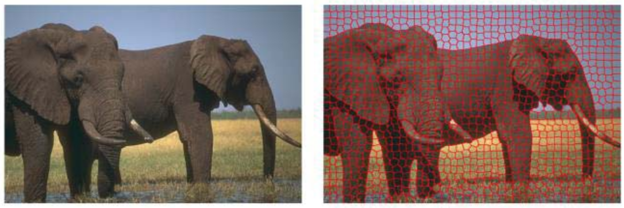
3.1 The super-pixel layer

The super-pixel layer replaces the pixel layer in the classic random walker algorithm and we would determine label value for every superpixel after computing the steady-state probability in superpixel layer. The super-pixel layer is consisted of many regions which are partitioned by over-segmentation algorithm [3] like in Fig 3(b). In Figure 3 (a) is the input image and Figure 3(b) is the superpixel image obtained from over segmentation. As Figure 3(b) shows, this step group pixels which have similar features in many regions from the input image. Every region is called superpixel in over-segmentation algorithm so we define this layer as the super-pixel layer. There are many methods [12] to generate superpixels. Each method has advantages and drawbacks. The over-segmentation algorithm generally have the following properties:

(1) Superpixels adhere well to object boundaries.

(2) Because superpixels are groups of pixels which have similar features, they can reduce computational complexity.

Based on these two properties, every region represent a node on the graph model and an edge exist if the two regions are adjacent. Because we consider every region as a node in the graph model, this action can save a lot of time instead of computing from millions of pixels. We find the label value in the super-pixel layer by using the random walks algorithm.



(a) (b)

Figure 3: (a) Input Image, (b) Superpixels after using over-segmentation algorithm.

3.2 The high-order layer

Besides the super-pixel layer, we design a high-order layer to give more information to the super-pixel layer and enforce label consistency inside the object boundary. In order to achieve this goal, we use the over-segmentation algorithm and an edge detection algorithm to design the high-order layer. In this step, we want to merge the region which may have similar features. We use the edge detection method [4] to find the edge from the image. The reason why we use edge detection is the superpixel would adheres well to image boundaries and we can merge some regions which might have similar features by using edge detection. After executing edge detection method, we can get a set of curves from the input image. The curves would indicate the boundary of an object.

3.3 Construct the graph model

In the phase, we would construct the graph model by using the super-pixels layer and the high-order layer. The graph model we propose is inspired on the paper [1]. It constructs a multi-layer graph model to solve image segmentation problem. One layer is based on pixel and the other is based on region. Our graph model use the super-pixel layer to replace the pixel-based layer and use the high-order layer to replace the region based layer. We define the graph model as an undirected graph G (V,E). The graph G contain node V = $\{X, Y\}$. The vertex $x_i \in X$ is the every region on super-pixel layer and the node $y_i \in Y$ is the merged regions in the high-order layer. The edge E = $\{E^X, E^Y, E^{XY}\}$ connects between the super-pixel layer and the high-order layer. $E^X \in E$ is the edge belong to the superpixel layer and $E^Y \in E$ are edges belong to high-order layer. $E^{XY} \in E$ is the edge which connect between the super-pixel layer and the high-order layer. An undirected edge exists, if the one of the following conditions is satisfied.

(1) The region in Figure 4 whose boundaries in black line are generated by the over- segmentation algorithm [3]. $E^x \subseteq E$ are the edge group on super-pixel layer. In E^X, an edge exist if two superpixels are adjacent. An edge $e_{S1S2} \in E^x$ between two superpixels s1 and s2 has a weight ω_{s1s2} .

The weight ω_{s1s2} is define as the typical Gaussion weighting function given by

$$\omega_{s1s2} = exp\left(-\frac{||g_{s1} - g_{s2}||^2}{\sigma}\right)$$

where g_{si} is the mean color of superpixels in si , i=1,2, and $g_{si} = \frac{1}{n_i}\sum_{c_i \in si} c_i$, n_i is the pixel number in superpixel si and c_i is the value in CIELAB color space.

(2) The green region is region which has been merged in the high-order layer in Figure 5. $E^y \subseteq E$ are the edge group on high-order layer. In E^Y , edge exist if two adjacent merged regions are connected like the black line between region m1 and m2. An edge $e_{m1m2} \in E^Y$ between two regions Y_{m1} and Y_{m2} has a weight ω_{m1m2} . The weight ω_{m1m2} is define as the typical Gaussion weighting function given by

$$\omega_{m1m2} = exp\left(-\frac{||g_{m1} - g_{m2}||^2}{\sigma}\right)$$

where g_{m1} is the mean color of merged superpixels in Y_{m1}, g_{s1} is the mean color of merged region in Y_{m1} and $g_{mi} = \frac{1}{n_i}\sum_{c_i \in Y_{mi}} c_i$, n_i is the pixel number in merged region y_i.

(3) Figure 6 is our whole graph model we build to handle image segmentation problem. $E^{xy} \subseteq E$ are the edge group between the super-pixel layer and high-order layer like the blue lines between two layers in Figure 6. In E^{XY}, the inter-layer connections are added using the fact that each superpixel corresponds to only one merged superpixel. An edge $e_{s1m1} \in E^{XY}$ between two superpixels Y_{s1} and Y_{m1} has a weight ω_{s1m1} . The weight ω_{s1m1} is defined as the typical Gaussion weighting function given by

$$\omega_{s1m1} = exp\left(-\frac{||g_{s1} - g_{m1}||^2}{\sigma}\right),$$

where g_{s1} is the mean color of superpixels in Y_{m1} and g_{m1} is the mean color of merged region in Y_i. Then we will use the graph model to solve image segmentation problem.

3.4 The random walker based on superpixels

The random walks algorithm [2] is the algorithm which used to solve image segmentation problem in our paper. This method start from user's scribble like in Figure 7 (a), the lines are labeled by the user. In this paper, we separate thee foreground object and the background from the input image so the user only use two colors to label the object. Red lines are the features for the foreground object and the green lines are for background. Each superpixel $x_i \in X$ and each merged region $y_i \in Y$ are labeled by user and the labeled region is called seed in random walker algorithm. The scribbled node is to assigned one label $l_k \in L \; where \; L = \{l_1, \dots, l_k\}$. In our method, we separate from the input image, so $L = \{l_1, l_2\}$. Different to classic random walks algorithm, the random walker with restarting have probability b back to seed. This strategy can solve weak boundary problem. The transition probability matrix in the random walk algorithm can be written as following:

$$P^{t+1} = (1-b)P^t * W + b * S$$

The matrix W is transition probability matrix which we define in the previous step. S is the matrix that denotes the seed point which is defined by user in the graph, b is constant which the value is 0.004 and P is the walk probability matrix. P^t is the walk probability matrix at time t from the random walker algorithm and P^{t+1} is walk probability matrix at time t+1. The time t=0~∞, P^0 is the seed initial matrix. When t=∞, we would get steady state by linear method as following equation.

$$P^{\infty} = b[I - (1-b)W]^{-1}S$$

Finally, we find the label value which have maximum probability from the seed l_k to node i as following equation:

$$R_i = argmaxP^{\infty}(l_k|x_i)$$

We would get the solution which is expressed in terms of the set of posterior probabilities $p(x_i|l_k)$. The posterior probabilities including the probability to the forground and the background for every superpixel. We find the largest probability and assign the label value to superpixel. Figure 7 (a) shows the image labeled by the user. We can decide every region would belong the foreground or the background like in Figure 7(b). Figure 7 (b) show our result from algorithm, green area are background and the other areas are foreground object.

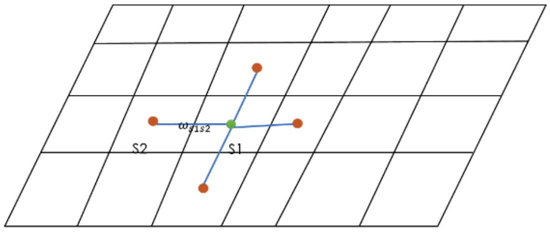


Figure 4:The proposed graph of the superpixel layer

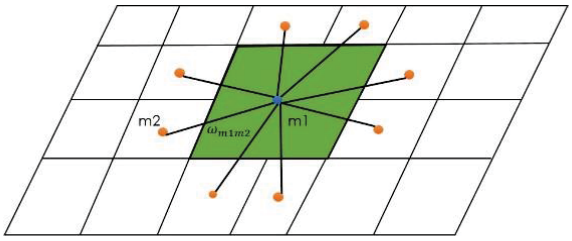


Figure 5: The proposed graph of the high-order layer

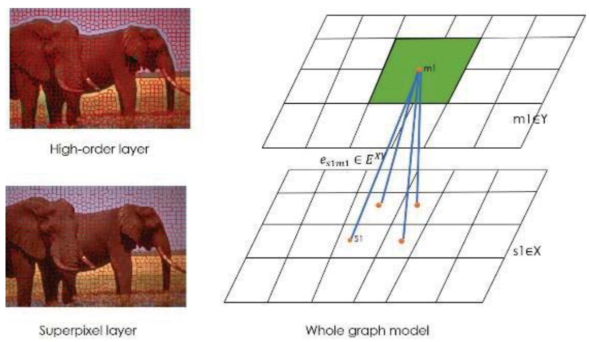
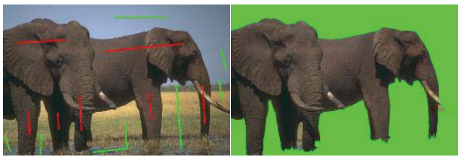


Figure 6: The graph model in our method

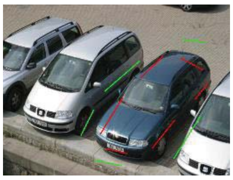
VI. Experimental Results

We have b=0.0004 in the random walker algorithm. The over-segmentation also need one parameter to decide how many superpixels would produce from input image. We set superpixel number parameter is 1200 to every input image from using over-segmentation [3]. Figure 8 (a) shows the input image and Figure 8 (b) shows the user's scribble. Figure 8(c) shows the segmentation by our method. Figure 8(d) and Figure 8(e) shows the segmentation by [1] and [2], respectively. We also used several natural images for testing and get satisfactory segmentation results

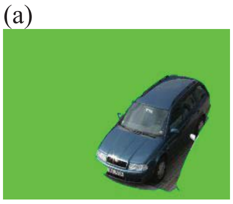


(a) (b)

Figure 7: The user's label image and output image (a) The image labeled by the user (b) The segmentation image of Figure 1(a) by the proposed algorithm.



(a) (b)



(c) (d)

Figure 8

(a)Input image, (b) User's scribble, (c) Our method, (d) ECCV 2008 [2], (e) CVPR 2010 [1].

(e)

IV. CONCLUSION

Our approach propose a new model for interactive image segmentation problem. We use the over-segmentation algorithm to save computational time and have satisfactory results

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