A Novel Marker Based Interactive Image Segmentation Method

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ABSTRACT
An important branch of computer vision is image segmentation. Image segmentation aims at extracting meaningful objects lying in images either by dividing images into contiguous semantic regions, or by extracting one or more specific objects in images such as medical structures. The image segmentation task is in general very difficult to achieve since natural images are diverse, complex and the way we perceive them vary according to individuals. For more than a decade, a promising mathematical framework, based on variational models and partial differential equations, have been investigated to solve the image segmentation problem. The proposed scheme is simple yet powerful and it is image content adaptive. With the similarity based merging rule, a two stage iterative merging algorithm was presented to gradually label each non-marker region as either object or background. We implemented the MSRM algorithm in the MATLAB.

I. INTRODUCTION

This new approach benefits from well-established mathematical theories that allow people to analyze, understand and extend segmentation methods. Moreover, this framework is defined in a continuous setting which makes the proposed models independent with respect to the grid of digital images. In color image segmentation seed selection, region growing and region merging are important stages. It should be noted that there is no single standard approach to perform seed selection, region growing, and region merging for color image segmentation. The appropriate technique is select on the basis of type of image and applications. Ugarriza *et al*. proposed a technique of initial seed selection. This technique uses vector field for edge detection and RGB to L*a*b conversion of image pixels to calculate the threshold by using adaptive threshold generation method. This method uses approximate calculation of threshold. The problem is that approximate calculation does not lead proper conclusion.

II. IMAGE SEGMENTATION

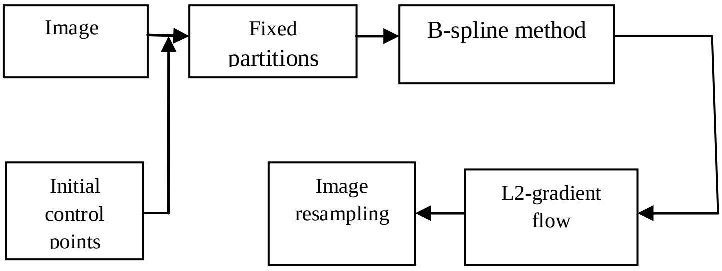
The problems of image segmentation and grouping remain great challenges for computer vision. Since the time of the Gestalt movement in psychology, it has been known that perceptual grouping plays a powerful role in human visual perception. A wide range of computational vision problems could in principle make good use of segmented images, were such segmentations reliably and efficiently computable. For instance intermediate-level vision problems such as stereo and motion estimation require an appropriate region of support for correspondence operations. Spatially non-uniform regions of support can be identified using segmentation techniques. Higher-level problems such as recognition and image indexing can also make use of segmentation results in matching, to address problems such as figure-ground separation and recognition by parts. Our goal is to develop computational approaches to image segmentation that are broadly useful, much in the way that other low-level techniques such as edge detection are used in a wide range of computer vision tasks.

- Thresholding
- Edge finding
- Seed region growing
- Region split and merging

In the analysis of the objects in images it is essential that we can distinguish between the objects of interest and "the rest." This latter group is also referred to as the background. The techniques that are used to find the objects of interest are usually referred to as *segmentation techniques* , segmenting the foreground from background. In this section we will present two of the most common techniques *thresholding* and *edgefinding* and techniques for improving the quality of the segmentation result. It is important to understand that: there is no universally applicable segmentation technique that will work for all images, and no segmentation technique is perfect.

III. GEOMETRIC FLOW METHOD

The block diagram of geometric flow method as shown below



Geometric flows, as a class of important geometric partial differential equations, have been highlighted in many areas, with Computer Aided Geometric Design is probably the field that benefited most from geometric flow methods. The frequently used geometric flows include mean curvature flow (MCF), weighted MCF, surface diffusion flow and Willmore flow etc. Different flows exhibit different geometric properties that could meet the requirement of various applications. The biharmonic equation, which is linear, has been used for interactive surface design. MCF and its variants, which are second order equations and also the most important and effective flows, have been intensively used for fairing and denoising surface meshes. MCF cannot achieve the G1 continuity at the boundary, thus for applications demanding high level of smoothness, higher order equations have to be used, e.g. the surface diffusion flow for surface fairing, and the Willmore flow for surface restoration, The construction of geometric flows is not a trivial task. In early days many geometric flows were manually manufactured by combining several geometric entities and differential operators, thus were lack of physical or geometric meaning. This drawback can be overcome by the construction of gradient descent flow. Gradient descent flow method can transform an optimization problem into an initial value (initial-boundary value) problem of an ordinary differential equation and thus is widely used in variational calculus. Constructing gradient descent flow needs to address two main issues, the definition of gradient and suitable choice of inner products. For a generic nonlinear energy functional, the gradient can be defined by Gˆ ateaux derivative. For the same energy functional, different inner products will generate different geometric flows, some of which have been mentioned above.

IV. MARKER BASED SEGMENTATION

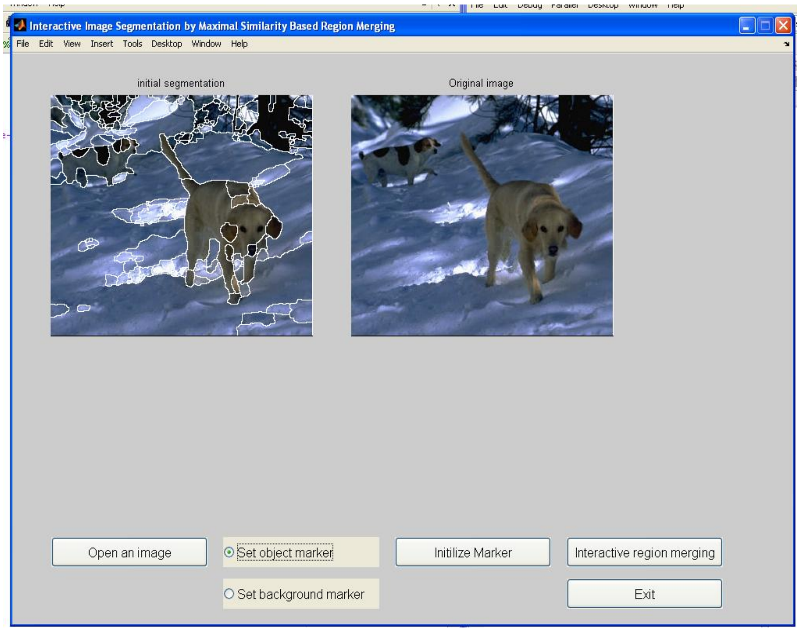
Efficient and effective image segmentation is an important task in computer vision and object recognition. Since fully automatic image segmentation is usually very hard for natural images, interactive schemes with a few simple user inputs are good solutions. This paper presents a new region merging based interactive image segmentation method. The users only need to roughly indicate the location and region of the object and background by using strokes, which are called markers. A novel maximal-similarity based region merging mechanism is proposed to guide the merging process with the help of markers. A region R is merged with its adjacent region Q if Q has the highest similarity with Q among all Q's adjacent regions. The proposed method automatically merges the regions that are initially segmented by mean shift segmentation, and then effectively extracts the object contour by labeling all the non-marker regions as either background or object. The region merging process is adaptive to the image content and it does not need to set the similarity threshold in advance.

Extensive experiments are performed and the results show that the proposed scheme can reliably extract the object contour from the complex background. In marker based segmentation, an initial segmentation is required to partition the image into homogeneous regions for merging. Any existing low level segmentation methods, such as super-pixel [13], meanshift [14,15], watershed [16] and level set [17], can be used for this step. In this paper, we choose to use the mean shift method for initial segmentation because it has less over segmentation and can well preserve the object boundaries. Particularly, we use the mean shift segmentation software—the EDISON System [18]—to obtain the initial segmentation map.

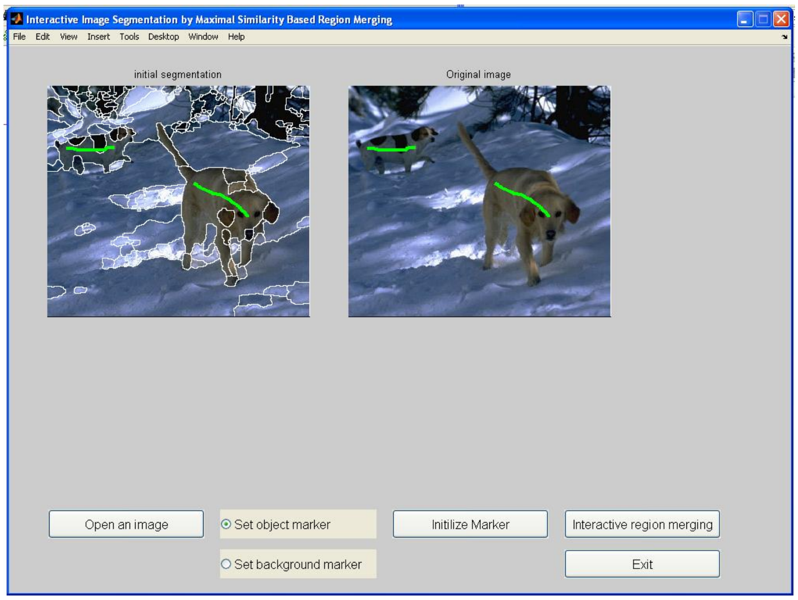
For detailed information about mean shift and the EDISON system, please refer to [19]. In this method, we only focus on the region merging. Several general-purpose algorithms and techniques have been developed for image segmentation. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a problem domain.

V. EXPERIMENTAL RESULTS

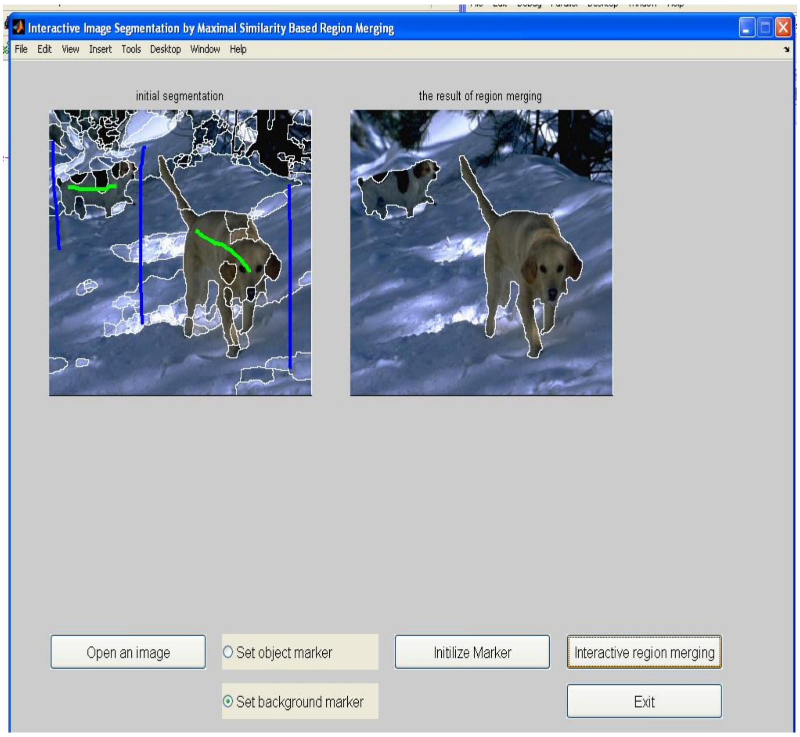
The execution time of the MSRM depends on a couple of factors, including the size of the image, the initial segmentation result, the user input markers and the content of the image. We implement the MSRM algorithm in the MATLAB 7.0 programming environment and run it on a PC with P4 2.6GHz CPU and 1024MB RAM.



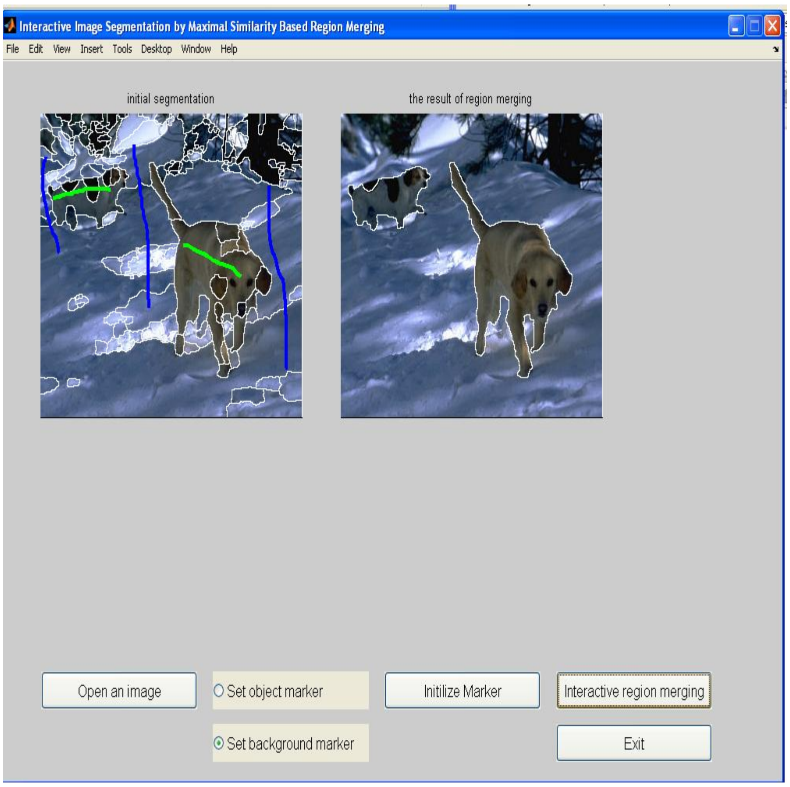
Click the set object marker radio button



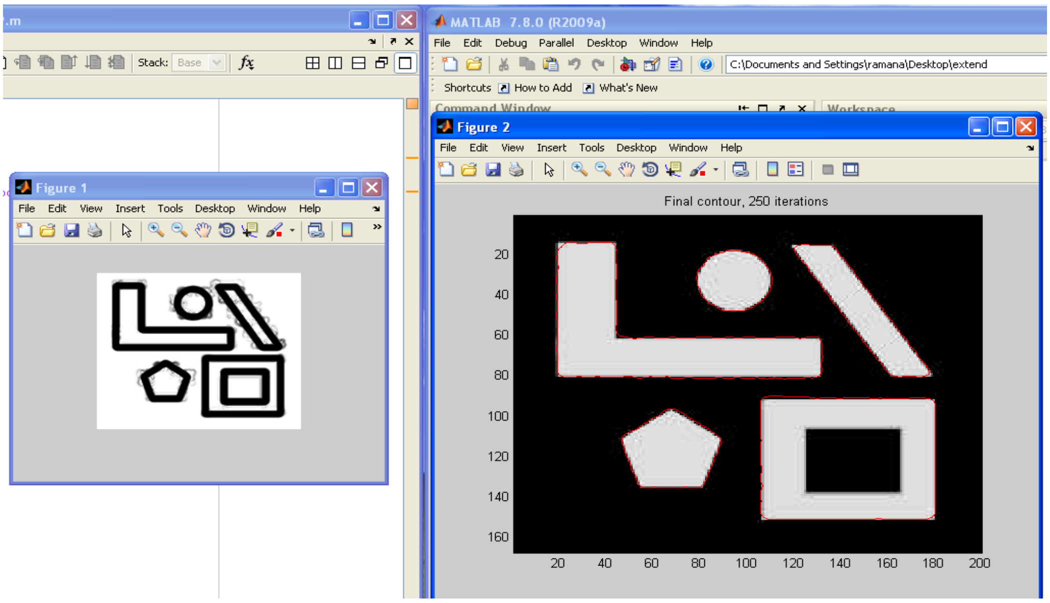
Mark the straight lines on dog objects



Click the set background marker radio button and then straight line(blue line) edges of dog objects and then click interactive region merging



Multiple object extraction: (a) initial mean shift segmentation and interactive information. The two green markers mark two objects. (b) The two extracted objects using the marker based segmentation method.



a) original image b) final segmentation result using geometric flow approach method

VI. CONCLUSION

This paper proposed a novel marker based interactive image segmentation method. The image is initially segmented by mean shift segmentation and the users only need to roughly indicate the main features of the object and background by using some strokes, which are called markers. Since the object regions will have high similarity to the marked object regions and so do the background regions, a novel maximal similarity based region merging mechanism was proposed to extract the object. The proposed scheme is simple yet powerful and it is image content adaptive. With the similarity based merging rule, a two stage iterative merging algorithm was presented to gradually label each non-marker region as either object or background.

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