INTERACTIVE FOREGROUND AND BACKGROUNG SEGMENTATION USING ACTIVE CONTOURS

G.Bhuvana.,(M.E), K.Radha., M.E.,(ph.d).,AP/CSE Muthayammal Engineering College,Rasipuram

E.Mailid: bhuvanait2012@gmail.com, kradhagokul@gmail.com

Mobileno:9842391220,9150399059

Abstract:

Video Segmentation is an important research topic in image processing. Interactive image segmentation algorithms are sensitive to the user inputs and often unable to produce an accurate boundary with a small amount of user interaction. They frequently rely on laborious user editing to refine the segmentation boundary. The proposed method exhibits many desirable properties of an effective interactive image segmentation algorithm, including robustness to user inputs and different initializations, the ability to produce a smooth and accurate boundary contour, and the ability to handle topology changes.

Index Terms—Interactive image segmentation, convex active contour, digital image editing.

1.INTRODUCTION:

Segmentation of video with background has been important research topic in intelligent surveillance and human-machine interface technologies,etc.In general, interactive image segmentation algorithms can be classified into two categories: boundary-based approaches and region-based approaches. In boundary-based approaches, the user is often asked to specify an initial area that is “close” to the desirable boundary. The active contours/Snake method, attempts to evolve an initial contour toward the object boundary.

Methods based upon intelligent scissors, apply Dijkstra’s shortest path algorithm to find a path between boundary seed points specified by the user. Considering that the boundary-based approaches require great care to specify the boundary area or the boundary points, especially for complex shapes, most recent interactive image segmentation algorithms take the regional information as the input. In particular, in region-based approaches, the user is often asked to draw two types of strokes to label some pixels as foreground or background, after which the algorithm completes the labeling of all other pixels.

In this paper, we consider the problem of interactive image segmentation with the input of foreground and background strokes, which requires only a small amount of interaction from the user.

2.RELATED WORKS

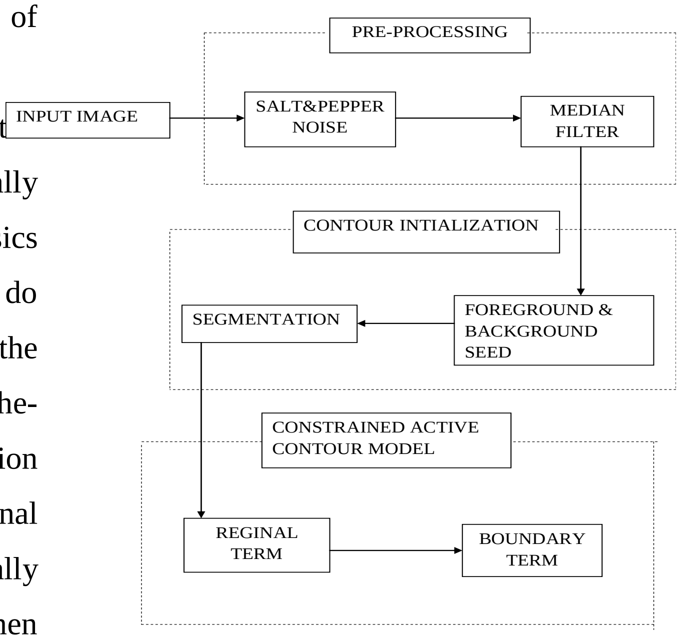
First, region-based methods are overly sensitive to small variations in the interactions provided by the user (see Fig. 1). As pointed out in [1], the Graph Cut algorithm is sensitive to the number of seeds, while the RW and Geodesic algorithms are sensitive to locations of seeds.

Second, the boundaries generat by the region-based approaches, especially those generated by RW and Geodesics based approaches, are often jaggy and do not adhere to the geometric features in the image (see Fig. 1).Most of the state-of-the-art interactive image segmentation methods [2],[3], [4], [5] rely on additional user inputs to either globally or locally refine the boundary. However, when dealing with complex images, the user is often required to provide a lot of additional strokes or boundary points and thus struggles with laborious refinement/editing.

As previously noted, the classical active contour model [6] is primarily used to perform local contour adjustment to improve the smoothness. The geodesic active contour model proposed in [7] is capable of evolving the entire boundary contour to snap to geometry edges, but it heavily depends on the edge detection function.

3.METHODOLOGY:

we describe the proposed constrained active contour method, which extends the convex active contour model of (1) (originally designed for automatic image segmentation)for interactive image segmentation.



A.Contour Initialization

For any active contour method, the contour needs to be initialized before the contour evolution process. Here, we use

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the segmentation result of the Geodesic method [5] for contour initialization due to its fast processing speed and the ability to avoid the "small-cut" problem.In particular, we represent the result of the Geodesic algorithm by a probability map P(x), whose value is within the range of [0,1] indicating the probability that pixel x belongs to the foreground region. In the Geodesic algorithm, for a pixel x, its geodesic distances to the foreground or background seed regions are computed, which are denoted as DF (x) and DB(x) respectively. Then, an estimate of the probability that the pixel x belongs to the foreground is calculated as

$$P(x) = \frac{D_B(x)}{D_F(x) + D_B(x)}.$$

B. Constrained Active Contour Model

As shown in (1), the convex active contour model consists of two terms: a regional term and a boundary term. Next,we discuss how to modify these two terms to incorporate the information from the user input and the initial segmentation result so as to ensure the refined contour complying with the user input.

1) **Regional Term Formulation**: The foreground and background seeds give an excellent description about the color distributions of the foreground and background regions.

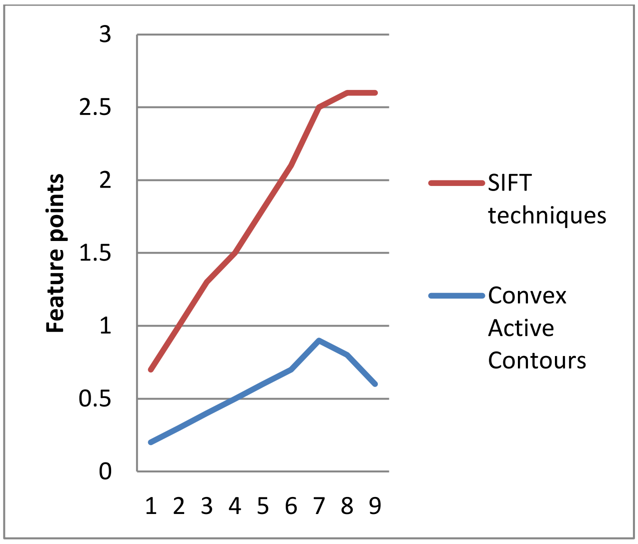
Foreground/background GMMs introduced in [8] are estimated from oreground/background seeds and used to represent the color distributions of the foreground and background regions.

2) **Boundary Term Formulation**: The boundary term of

$$\int_\Omega g_b(x)|\nabla u|\,dx$$

is essentially a weighed total variation of function u, where the weight gb plays an important role.

PERFORMANCE EVALUATION:



4.RESULT DISCUSSION

In this paper, we have proposed a robust and accurate interactive image segmentation method based on the continuous domain convex active contour model. We have demonstrated that our method outperforms the state-of-the-art interactive segmentation methods. It exhibits many desirable properties for a good segmentation tool, including the robustness to user inputs and different initializations, the ability to produce a smooth and accurate boundary contour, and the ability to handle topology changes. Our method runs very fast due to the fact that the proposed constrained active contour model can be solved quickly by a fast Split Bergman method, and the adoption of the Geodesic algorithm for initialization. We would like to point out that although the proposed constrained active contour model was able to automatically optimize an initial contour, it can also take additional user inputs for further user-guided contour evolving. This was especially necessary in either the case that the initial contour is very poor or the case that a highly accurate result is sought.

This paper can be extended in a few ways. For example,it might be beneficial to apply the continuous-domain convex active contour model for other segmentation problems, such as image matting or video segmentation.

5.REFERENCES

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