Constrained Active Contour For Interactive Image Segmentation

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Abstract

Interactive image segmentation algortihms incorporates small amount of user interaction to define the desired content to be extracted, has received much attention in the recent years. We propose a robust and accurate interactive method based on the recently developed continuous-domain convex active contour model. The proposed method exhibits many desirable properties of an effective interactive image segmentation algorithm, including robustness to user inputs and different initializations with an efficient and light-weight solution for rendering smooth shadow boundaries that do not reveal the tessellation of the shadow-casting geometry. Our algorithm reconstructs the smooth contours of the underlying mesh and then extrudes shadow volumes from the smooth silhouettes to render the shadows. For this purpose we propose an improved silhouette reconstruction using the vertex normal of the underlying smooth mesh. Then our method subdivides the silhouette loops until the contours are sufficiently smooth and project to smooth shadow boundaries. Here we solve the two problems in a unified framework. Gradient controlled partial differential equation (PDE) surfaces to express terrain surfaces, in which the surface shapes can be globally determined by the contours, their locations, and height and gradient values. The surface generated by this method is accurate in the sense of exactly coinciding with the original contours and smooth with C1 (contour active convex region) continuity everywhere. The method can reveal smooth saddle shapes caused by surface branching of one to more and can make rational interpolated sub-contours between two or more neighbouring contours.

Keywords— contour, interpolation, mesh. silhouette, shadow-casting, gradient

I) INTRODUCTION

Interactive image segmentation, incorporates small amount of user interaction to define the desired content to be extracted, has received much attention in the recent years. Already many interactive image segmentation algorithms have been proposed. In general, interactive image segmentation algorithms can be classified into two categories: boundary-based approaches and region-based approaches.

Boundary-based approaches, the user is often asked to specify an initial area that is “close” to the desirable boundary.

The "active contours" start with an initialized contour and actively deform themselves to the desired border while reducing the defined energy in each iteration until convergence.The active contours/Snake method [2] proposes the top down approach instead of using previous bottom up approaches and it attempts to evolve an initial contour toward the object boundary. To find a path between boundary seed points specified by the user Dijkstra’s shortest path algorithm is applied in the methods based upon intelligent scissors [3], [4]

Boundary-based approaches requires 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 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. The region based interactive segmentation algorithms, includes RandomWalks based Methods [7]–[9], Graph Cut-based methods [5], [6], and Geodesic methods [10], [11]. All the above methods basically treat an image as a weighted graph with the nodes corresponding to pixels in the image and edges being placed between neighboring pixels, and to minimize a certain energy function on the graph for producing segmentation.

In 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. First the region-based methods are overly sensitive to small variations in the interactions provided by the user As in [12], the Graph Cut algorithm is sensitive to the number of seeds, while the Random Walk and Geodesic algorithms are sensitive to locations of seeds is mainly due to the different behaviors of the different energy functions.

The boundaries generated by the region-based approaches, especially those generated by RW and approaches based on the geodesic, are often jaggy and they do not adhere to the geometry features present in the image additional refinement step is often needed to improve the segmentation performance of the region-based methods. Most of the state-of-the-art interactive image segmentation methods [6],[7], [9], [10] 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. Another way for boundary refinement is to use the active contours/Snakes model [1] to refine the initial boundary contour produced by a region-based segmentation approach. The refinement based on Snakes is only able to change the contour locally for smoothness but the approach is incapable of evolving the entire contour to snap to geometry features/edges, and also incapable of handling topology changes of the evolving contour.

The mathematical tool of the new method is the continuous-domain convex active contour model [14], which makes use of both the boundary and the regional information to find a global "optimal" solution. Continuous-domain convex methods have started to receive attention since they avoid the inherent grid bias in all discrete graph-based methods, and also have fast and global numerical solvers through convex optimization [15], [16]. However, the convex active contour model so far has mainly been applied for automatic image segmentation, which often results in over-segmentation with trivial solutions for complex images [14], [16].

The major contribution of this includes the following.

The powerful continuous-domain convex active contour with one of the region based methods, Geodesic/random walk where the region-based method is used in the first step to generate an initial contour, and the convex active contour is then applied to optimize the contour. Such integration utilizes the seed propagation and the location features introduced by Geodesic/Random Walk to reduce the possible "small cut" problem in the convex active contour, and also the powerful contour evolving capability provided by the convex active contour model to absorb the non robustness of the region-based approaches. Then our method subdivides the silhouette loops until the contours are sufficiently smooth and project to smooth shadow boundaries.

II) CONSTRAINED ACTIVE CONTOUR MODEL

In this we describe the continuous domain convex active contour model which extends the convex active contour model.

A. Preprocessing

Preprocessing images commonly involves removing low-frequency background noise, normalizing the intensity of the individual particles images, removing reflections, and masking portions of images. Image preprocessing is the technique of enhancing data images prior to computational processing. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing .Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

B. Initialization of Contour

Initialization of contour is done using the region based method. Based on the initialized contour pre segmented output is obtained. In this using the region based method value similarity and spatial similarity is calculated and pre segmented output is obtained by initializing the contour.

C. Convex Active Contour Model

The convex active contour model consists of two terms: a regional term formulation and boundary term formulation.

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 Gaussian mixture models (GMMs) introduced in [20] are estimated from foreground/background seeds, and used to represent the color distributions of the foreground and background regions. Let $Pr(x|F)$ and $Pr(x|B)$ denote the probabilities that pixel x denotes the foreground and background GMMs, respectively.

$$PF(x) = -\log Pr(x|F)/-\log Pr(x|F) - \log Pr(x|B)$$

and

$$PB(x) = -\log Pr(x|B)/-\log Pr(x|F) - \log Pr(x|B). \quad \textbf{(2)}$$

We incorporate this regional information derived from foreground/background strokes into the regional term of the convex active contour model as $hr(x) = PB(x) - PF(x)$. **(3)**

This definition of hr ensures that the active contour evolves toward the one complying with the known GMM models. For instance, for a pixel x, if $PB(x) > PF(x)$ (respectively, $PB(x) < PF(x)$) and $PB(x) - PF(x)$ is positive (respectively, negative), $u(x)$ tends to decrease (respectively,increase) during the contour evolution in order to minimize (1),which can lead to $u(x) \leq T$ (respectively, $u(x) > T$) and the classification of the pixel belonging to the background (respectively, the foreground).

The hr definition of (3)fails in the case that the foreground and background color models are not well separated. Thus, to avoid this problem and also to make use of the segmentation result obtained by the Geodesic algorithm in step 1, we further propose to incorporate the probability map $P(x)$ into the region term hr as

$$hr(x) = \alpha(PB(x) - PF(x)) + (1 - \alpha)(1 - 2P(x)) \quad (4)$$

where α, $\alpha \in [0, 1]$, is a tradeoff factor. The second term $(1-2P(x))$ in (10) prevents the refined contour drifting too far apart from the initial segmentation. Specifically, when $P(x) > 0.5$ and $(1 - 2P(x))$ are negative, $u(x)$ tends to increase in order to minimize (1), which favors classifying the pixel as a foreground pixel, and vice versa.

In addition, it can be observed that when $hr(x) \to +\infty$(respectively, $hr(x) \to -\infty$), the regional term forces $u(x) = 0$ (respectively, $u(x) = 1$) to minimize This observation allows us to enforce some hard constraints in the contour evolution process. In particular, for those pixels that have no ambiguity in classification, including the pixels lying on the foreground/background strokes and the pixels having very large or very small $P(x)$ values ($P(x) > 0.9$ or $P(x) < 0.1$), we treat them as hard constraints in the contour evolution process. We directly assign a negative hr value and a positive hr value, both with extremely large magnitude, to these confirmed foreground and background pixels, respectively. In this way, we guarantee that the refined result complies with the user input and also exploit more information from the initial segmentation result.

2) Boundary Term Formulation:

The boundary term of $\int_\Omega gb(x)|\nabla u|\, dx$ in (1) is essentially a weighed total variation of function u, where the weight gb plays an important role.The definition of gb in is effective in the sense that it encourages the segmentation along the curves where the edge detection function is minimal. The problem with is that at locations with weak edges the boundary is likely to be smoothed out. Thus, in this paper, we propose to incorporate the GMM probability map $PF(x)$ to enhance the edge detection. Particularly, we define gb as

$$gb = \beta \cdot gc + (1 - \beta) \cdot ge \quad (6)$$

where gc and ge are the results of applying the edge detection to the GMM probability map $PF(x)$ and the original image, respectively, and β, $\beta \in [0, 1]$, is a tradeoff factor computed in a similar way as α given above formula.

D. Constrained Active Contour Model

Based on the above calculated values the constrained active contour model is constructed, based on the calculated values Compute the alpha channel inside the band, once distance is obtained. Estimate Foreground and Background components in Luv space for each pixel inside the band, after matte alpha is computed. With these components we can paste the object onto a new Background if desired with no noticeable visual artifacts by the simple matting equation.

E. Silhouette Reconstruction

A silhouette is the image of a person, an object or scene represented as a solid shape of a single color, usually black, its edges matching the outline of the subject. The interior of a silhouette is basically featureless, and the whole is typically presented on a light background, usually white, or none at all.

The silhouette differs from an outline which depicts the edge of an object in a linear form, while a silhouette appears as a solid shape. Silhouette images may be created in any visual artistic media.

Our algorithm reconstructs the smooth contours of the underlying mesh and then extrudes shadow volumes from the smooth silhouettes to render the shadows. For this purpose we propose an improved silhouette reconstruction using the vertex normal of the underlying smooth mesh. Then our method subdivides the silhouette loops until the contours are sufficiently smooth and project to smooth shadow boundaries. Here we solve the two problems in a unified framework. Gradient controlled partial differential equation (PDE) surfaces to express terrain surfaces, in which the surface shapes can be globally determined by the contours, their locations, and height and gradient values. The surface generated by this method is accurate in the sense of exactly coinciding with the original contours and smooth with C1 (contour active convex region) continuity everywhere. The method can reveal smooth saddle shapes caused by surface branching of one to more and can make rational interpolated sub-contours between two or more neighboring contours.

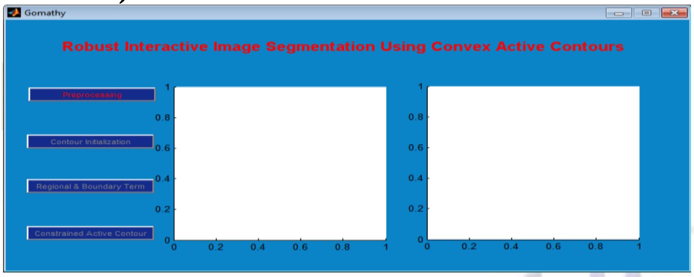
III) CONCLUSION

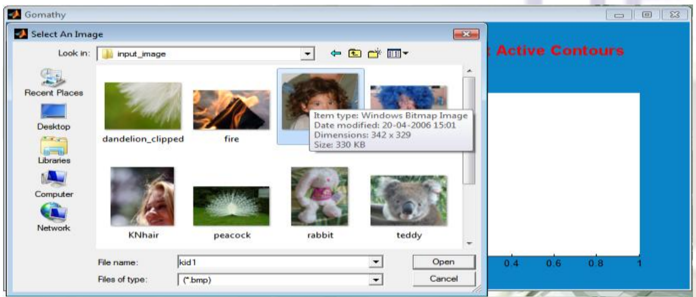
In this paper, we have proposed a robust and accurate interactive image segmentation method based on the continuous domain convex active contour model. We have demonstrated that our method outperforms the state-of-the-art interactive segmentation methods. It exhibits many desirable properties for a good 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. In this we also proposed improved silhouette reconstruction for handling sophisticated shapes

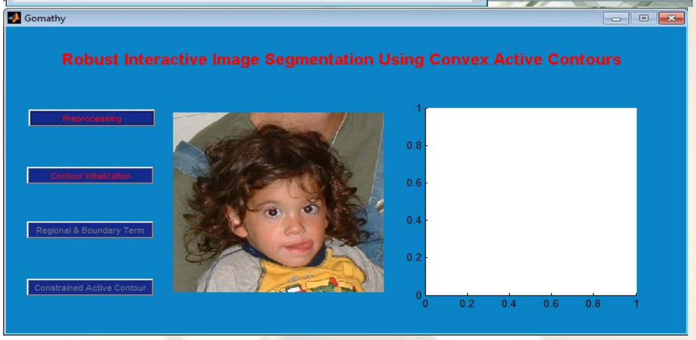
IV) FUTURE WORK

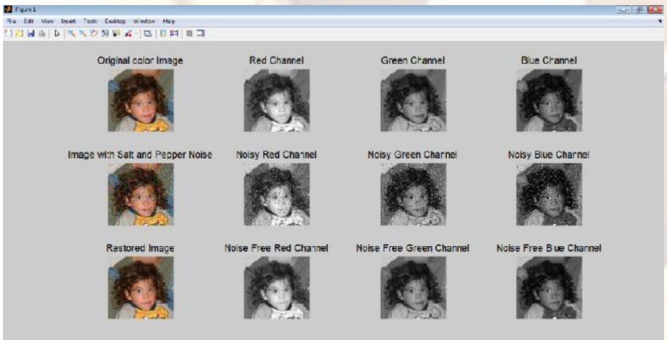
This paper can be extended in a few ways. For example, it might be beneficial to apply the continuous-domain convex active contour model for other segmentation problems, such as image matting or video segmentation.

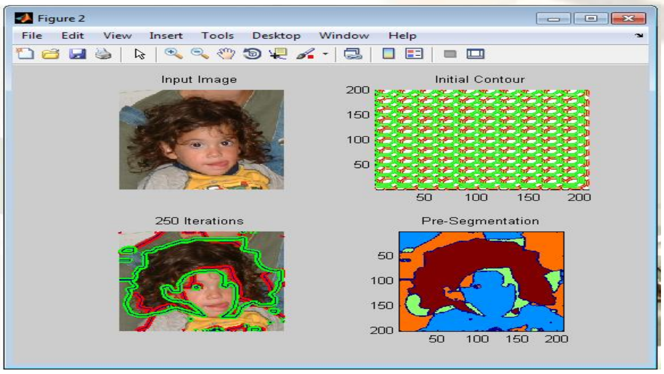
V) RESULTS

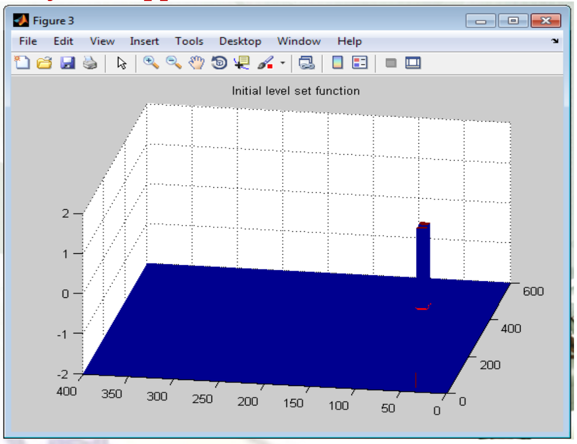


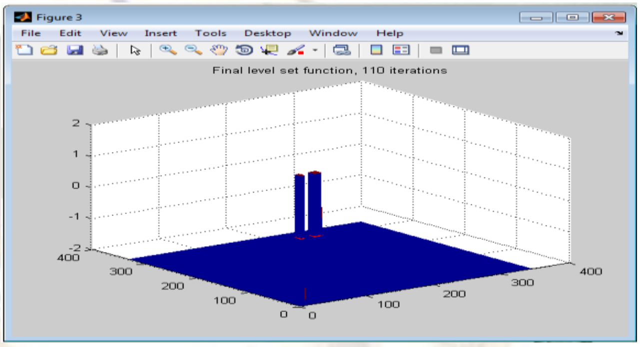


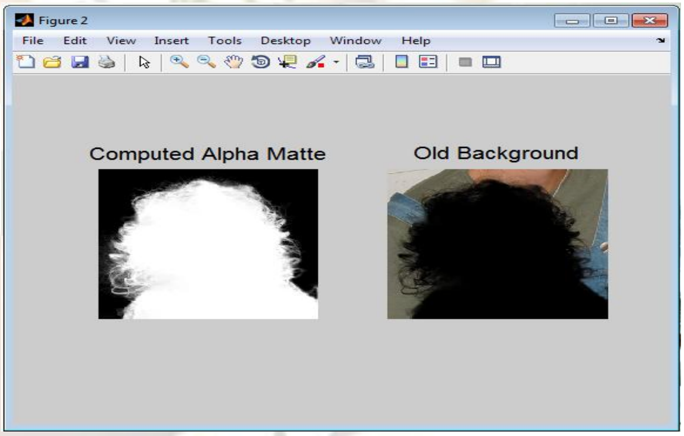


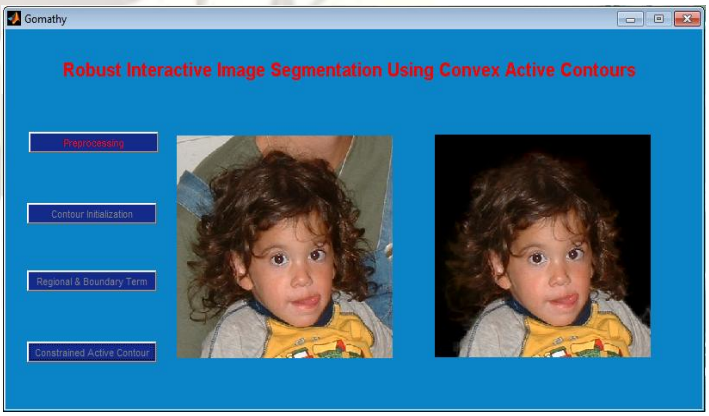












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