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A simple boundary reinforcement technique for segmentation without prior ☆

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ABSTRACT

Accurate boundary detection is a critical step of the image segmentation process. While most edge detectors rely on the presence of strong intensity gradients, this criteria can limit robustness in many real world cases. In this work we propose a scheme which makes use of a combination of both global and local segmentation methods to capture the boundary of target objects in low contrast images. This approach has several advantages: the globally convex segmentation scheme is immune from initial conditions and is easily adapted to the data. The addition of a segmentation scheme based on local curve evolution produces a solution which is shown to help preserve topology between the initial and target shape, a property lacking in globally convex segmentation schemes. Experimental results show that the proposed method achieves enhanced performance compared to classical data-driven segmentation schemes proposed in the literature.

1. Introduction

Image segmentation is arguably one of the most important tasks in computer vision and has been an active area of research over the last three decades. Efforts directed at this task have included variational approaches, statistical and more recently combinatorial methods. Many of the most successful segmentation methods have been formulated as energy minimization problems in which the key object detection criteria are incorporated into the energy functional.

One of the first proposals to cast image segmentation as an energy minimization problem was the approach of [11] who computed the segmentation of a given image by evolving curves in the direction of the negative energy gradient using appropriate partial differential equations. In this approach, boundaries are detected using the strength of the gradient at each pixel. In [11] the curve is represented explicitly, which can lead to some drawbacks, in particular in order to avoid self-intersection and overlap of contour points, reparameterization is required. Similarly, sophisticated reparameterization schemes are needed to handle topological changes, which are necessary for segmenting multiple objects or objects with an unknown topology.

To overcome the need for reparameterization, techniques based on implicit curve evolution theory [15,3] allow for motion based on geometric measures such as unit normal and curvature. To obtain a new length constraint which is independent of parameterization, Caselles et al. [3] and Kichenassamy et al. [12] simultaneously proposed the implicit geodesic active contour, the energy functional of which is given by:

$$E(C) = \int_0^1 g(|\nabla I(C(q))|)|C'(q)|dq \tag{1}$$

$$\text{where} \quad g = \frac{1}{1+\beta|\nabla I|^p} \quad \text{with } p = 1 \quad \text{or} \quad 2$$

If we let Ω denote the image domain, where $\Omega \subset \mathbf{R}^N$ then in the above equation, the image is represented by, $I:\Omega \to \mathbb{R}, C(q):[0,1] \to \Omega$ represents the curve, while β controls the sharpness of the detected edges. In the level set method of Osher and Sethian [15], the curve is represented implicitly as the zero level line of some embedding function $\phi:\Omega \to \mathbb{R}$: $C = \{x \in \Omega \mid \phi(x) = 0\}$ where $\phi(x) \leqslant 0$ in the interior of the curve and $\phi(x) > 0$ in the exterior. The level set method evolves a curve by updating the level set function at fixed coordinates through time, rather than tracking a curve through time, as in a parametric setting. In an implicit formulation, both topological changes and also extension to higher dimensions are handled naturally.

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Another energy minimization approach for detecting edges in an image is the Mumford–Shah model [14], which in its most general form seeks both an edge set and an approximation of the image which is smooth everywhere except across the edge set. There has been a considerable amount of research on computing minimizers by numerical algorithms. In [5,23] the authors presented a level-set formulation of the piecewise constant variant of the Mumford–Shah model. Considering an image with two regions, the object to be segmented is denoted S and the background denoted $\Omega \setminus S$, the authors proposed the following model:

$$\min_{S,c_1,c_2} \int_{\Omega\setminus S} |I(x) - c_1|^2\, dx + \int_S |I(x) - c_2|^2\, dx + \nu|\partial S|. \tag{2}$$

The last term of the energy functional is the length of the boundary of S weighted by the parameter ν, while the first terms represent the data-fidelity where c_1 and c_2 are two scalars that attempt to approximate the image in the interior and exterior region. In order to find a minimizer by a numerical algorithm, it was proposed in [5,23] to represent the partition with a level set function, resulting in the following problem:

$$\min_{\phi,c_1,c_2}\left(\int_\Omega |I(x,y) - c_1|^2 H(\phi)dx + \int_\Omega |I(x,y) - c_2|^2(1 - H(\phi))dx + \nu\int_\Omega |\nabla H(\phi)|dx\right) \tag{3}$$

where H is the Heaviside function, defined such that $H(z) = 1$ if $z \geqslant 1$ and $H(z) = 0$ if $z < 0$ and is used to select either the interior or exterior of the curve. This work is known as Active Contours without Edges (ACWE) or Chan-Vese (CV) method. More recently, efficient convex optimization algorithms have been developed which result in global minimizers, e.g. the Split Bregman algorithm [9] and continuous max-flow [26,27].

To increase robustness, schemes have been proposed which combine region and edge terms [16,1]. In [16], an energy minimization approach for tracking objects was proposed, where regional and edge information were integrated in separate terms of an energy functional, in addition to a motion based term. In order to solve the resulting minimization problem, the level set method was applied. The quality of segmentation often depends on the quality of the detected edges. Bresson et al. [1] proposed a method which combines the data fidelity term of the ACWE model and the edge attraction term of the geodesic active contour (GAC) model in a global minimization framework.

Another line of research attempts to minimize the full Mumford–Shah model with curves that contain endpoints in order to detect edges. The Mumford–Shah model and the GAC model were extended to include more general edge sets in [22,21]. In [24], the authors represented the edges by a binary function, leading to a non-convex minimization problem closely in spirit to the phase field representation. A convex relaxation of the piecewise smooth Mumford–Shah model was proposed in [18], by lifting the the problem to a higher dimensional space. Although computationally expensive, this approach has the advantage of converging to a close approximation of a global minimizer, without getting stuck in a local minimizer. In [2] a generalization of the Mumford–Shah model was proposed with an extra term which enforced closeness between the gradient of the reconstructed image and the original image. The motivation behind this model is to better reconstruct edges with low contrast changes. A numerical algorithm based on the level set method was proposed. Closely related is also the diffusion equation of Perona and Malik [17], which converges to a local minimizer of the Mumford–Shah model if an appropriate data fitting term is added.

In Rajpoot et al. [19] an intensity invariant, real-time method was proposed to extract boundary information by analyzing the monogenic signal [7]. The proposed filter uses a local phase based method to extract edge information. The method produces a finer edge extraction than gradient detectors; however, due to its intensity invariance, tends to over-segment the image. Another approach for generating feature detectors proposed for application to echocardiography, is the method of Mulet-Parada et al. [13], a 2D + T method, in which it was demonstrated that a local phase-based approach produces more accurate edge results than conventional gradient magnitude methods.

The problem we addressed in the current work was how to increase segmentation robustness using a purely data driven approach. Incorporating prior information into a segmentation scheme is of course an advantage if such information exists, however this is not always the case; with this in mind, in the current work we sought to develop a method for images with weak boundaries by looking at new ways to incorporate pre-existing information. In the preliminary conference paper [6], a combination technique was presented using Geometric Split Bregman method with a topology preserving level set technique for application to echocardiography with the similar objective of detecting low-contrast boundaries. The method described here similarly proposes a sequential model using a global segmentation scheme, however in this work we make use of the alternate formulation using continuous maximum flow method while using the Geodesic Active Contour method to capture the final boundary. Similarly to [24,2], we also apply a variation of the Mumford Shah model to improve the edge detection step. While in [24] the goal was to improve the 'standard' canny edge model, our proposal is to delineate structures with low contrast boundaries by reinforcing the weak edges.

To summarize our contributions, in this paper we propose:

1. A new technique for generating an edge detector function which exploits the natural properties of the Mumford–Shah functional to effectively reinforce weak boundaries.
2. A combination of the proposed edge detector with the GAC method and demonstrate its applicability to images with weak edges, such as echocardiography medical images.

The remainder of the paper is organized as follows: In Section 2, we describe the proposed segmentation model. Section 3 contains experimental results on both medical and non-medical real images. Section 4 presents the discussion of the results and Section 5 concludes the paper.

2. Methodology

In this paper we propose a sequential model which addresses some of the weaknesses of these previous methods. The type of images focused on in this work often have weak edges and boundaries. Therefore, an edge detection method based directly on the image gradients is not expected to work well. In order to obtain a clearer edge map, we first approximate the image by a piecewise constant function, by efficiently computing a global minimizer to the model (2) with the Continuous Maximum Flow (CMF) algorithm [26,27] Then in order to obtain a single curve which captures the boundary of the object, we apply the geodesic active contour (GAC) method where the edge attraction term is constructed from the edge map in the first step.

2.1. Computation of edge detector from global segmentation output

The first step of our method is to extract a rough edge map by using the ACWE model with two regions. In recent work, efficient algorithms have been proposed for computing global minima to this model. In [4] it was shown that (2) can be exactly minimized via the convex problem