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Active contours textural and inhomogeneous object extraction

Lutful Mabood [a], Haider Ali [a,*], Noor Badshah [b], Ke Chen [c], Gulzar Ali Khan [a]

[a] Department of Mathematics, University of Peshawar, Pakistan
[b] Department of Basic Sciences, UET Peshawar, Pakistan
[c] Department of Mathematical Sciences, The University of Liverpool, UK

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ABSTRACT

A new selective segmentation active contour model is proposed in this paper that embeds an enhanced image information. By utilizing the average image of channels (AIC), which handles texture and noise, our model is capable to selectively segment and capture objects with nonuniform features. Moreover, the AIC is fitted with linear functions which are updated regularly to accurately guide the level set function to handle nonconstant intensities. Furthermore, we employ prior information in terms of geometrical constraints which work in alliance with image information to capture objects with intensity inhomogeneity. Experiments show that the proposed method achieves better results than the latest selective segmentation models. In addition, our approach maintains the performance on some hard real and synthetic color images.

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1. Introduction

Image segmentation is one of the most important and complicated task in the field of image processing and computer vision. Many different approaches are introduced in the literature including PDE-based active contour models [8,14] for curve evolution which has gained much popularity among the researchers. The active contour methods use a partial differential equation (PDE) to model and track how fronts evolve in a discrete domain by maintaining and updating a distance field to the fronts. This method can be categorized as the edge-based methods [3,4,11,12] and region-based methods [1,9,18,22,27]. The edge-based models use edge information to guide the active contours towards the object boundaries, whereas, region based models use statistical region data of an image. In particular, the Mumford–Shah (MS) model [18] is a milestone in the region based segmentation models.

For a given image $z=z(x,y)$, the MS model for segmentation solves

$$\min_{z_0,\Gamma} F(z_0,\Gamma)^{MS}=\mathcal{H}^{n-1}(\Gamma)+\|z-z_0\|^2_{L_2(\Omega)}+\alpha\int_{\Omega-\Gamma}|\nabla z_0|^2dx\,dy \qquad (1)$$

for the reconstruction of the ideal image $z_0(x,y)$ over domain Ω, where Ω is a bounded subset of $\mathbb{R}^n$ with Lipschitz boundary and the feature boundary set Γ. The term $\mathcal{H}^{n-1}$ is the $n-1$ dimensional Hausdorff measure, which in the 2-dimensional case $\mathcal{H}^1$ denotes the length of the curve. Since the term $\mathcal{H}^{n-1}$ causes computational complexity in the MS functional, therefore a natural way to approximate MS functional was introduced by Chan–Vese (CV) [9], which implemented the piecewise segmentation:

$$F^{2D}_{CV}(\Gamma,c_1,c_2)=\mu.\mathcal{H}^1(\Gamma)+\lambda_1\|z-c_1\|^2_{L_2(\Omega_{in})}+\lambda_2\|z-c_2\|^2_{L_2(\Omega_{out})}, \qquad (2)$$

where c_1 and c_2 are average values of z respectively in Ω_{in} (i.e., inside Γ) and in (Ω_{out}) (i.e., outside of Γ). In level set formulation Eq. (2) takes the form

$$F^{2D}_{CV}(\phi,c_1,c_2)=\mu\mathcal{H}^1(\phi)+\lambda_1\|z-c_1\|^2_{L_2(\Omega_{in})}+\lambda_2\|z-c_2\|^2_{L_2(\Omega_{out})},$$

where

$$\mathcal{H}^1(\phi)=\int_\Omega\delta(\phi)|\nabla\phi|\,dx\,dy,$$

$$\|z-c_1\|^2_{L_2(\Omega_{in})}=\int_\Omega|z(x,y)-c_1|^2H(\phi)dx\,dy,$$

$$\|z-c_2\|^2_{L_2(\Omega_{out})}=\int_\Omega|z(x,y)-c_2|^2(1-H(\phi))dx\,dy.$$

Since the Heaviside function, H, is not differentiable at the origin, a regularized version of Heaviside function is used [9,10,20,21],

$$H_\epsilon(w)=\frac{1}{2}\left(1+\frac{2}{\pi}\arctan\left(\frac{w}{\epsilon}\right)\right),\qquad \delta_\epsilon(w)=H'_\epsilon(w)=\frac{\epsilon}{\pi(\epsilon^2+w^2)}.$$

A simple extension to the CV model is to use linear approximation instead of constant [23]. This model is more appropriate when the image has region of linear shading instead of piecewise

* Corresponding author.
E-mail addresses: lathizm@gmail.com (L. Mabood), haider_uop99@yahoo.com (H. Ali), noor2knoor@gmail.com (N. Badshah), k.chen@liv.ac.uk (K. Chen), mshahkar95@yahoo.com (G.A. Khan).

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constant intensities:

$$F^{2D}_{Linear}(\phi, a_i, b_i) = \mu . \int_{\Omega} \delta(\phi) | \nabla \phi | \, dx \, dy + \lambda_1 \| z - (a_0 + a_1 x + a_2 y) \|^2_{L_2(\Omega_{in})} + \lambda_2 \| z - (b_0 + b_1 x + b_2 y) \|^2_{L_2(\Omega_{out})} \quad (3)$$

where a_i, b_i, where $i = 0, 1, 2$ are coefficients of linear functions.

The a_i can be computed by linear system:

$$\frac{\partial}{\partial a_i} \| z - (a_0 + a_1 x + a_2 y) \|^2_{L_2(\Omega_{in})} = 0, i = 0, 1, 2, \quad (4)$$

whereas similar solution procedure follows for b_i. Several recent generalization and variants [2,16,15,19,24,25] of the CV model can be seen which have shown better results in bias field correction, texture and noise. However, these aforementioned segmentation models are not designed for segmenting a particular object of interest and not all objects in it. Thus selective segmentation is a task in which an object/region of interest is detected, given additional information of geometric constraints in the form of list of points near the object/region. Motivated from the work in [11,12], we recently proposed two mixed models of edge based and region-based methods that are more robust for noisy images [3] and when edges are not prominent [4]. However, these models were not designed for texture and inhomogeneity.

In this paper, we propose a novel active contour model (ACM) which embeds AIC, an enhanced version of a given image for robust guidance of the contour to capture, objects with diffuse edges, objects with noise and textural detail. Furthermore, the AIC is approximated with linear functions to handle varying intensity objects. Experiments show that the proposed method achieves better results than the latest selective segmentation models. Moreover, the proposed approach maintains the performance in real and synthetic color images.

The rest of the paper is organized as follows. Section 2 reviews some latest selective segmentation models. Section 3 exhibits the proposed new model. Section 4 reveals an additive operator splitting (AOS) method for solving the resulted PDE. Section 5 displays some experimental tests with competing models. Conclusion is made in Section 6.

2. The Badshah–Chen model (BC)

To capture a particular object of interest, the Badshah and Chen (BC) [3] proposed the following functional for minimization

$$F^{2D}_{BC}(\phi, c_1, c_2) = \mu \int_{\Omega} d(x,y) g(|\nabla z|) \delta(\phi) | \nabla \phi | \, dx \, dy + \lambda_1 \| z - c_1 \|^2_{L_2(\Omega_{in})} + \lambda_2 \| z - c_2 \|^2_{L_2(\Omega_{out})}, \quad (5)$$

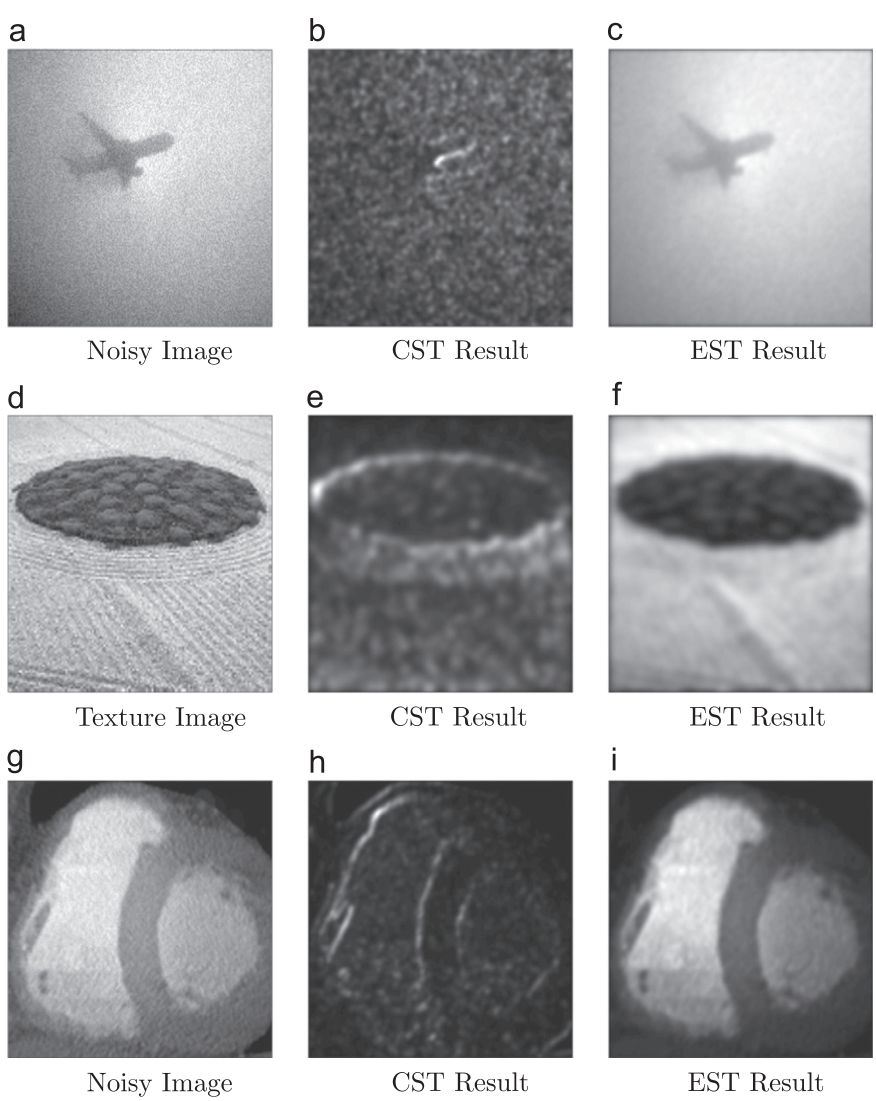

Fig. 1. Results of CST and EST on noisy and textural images.

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