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Robust global and local fuzzy energy based active contour for image segmentation

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ABSTRACT

Though various image segmentation techniques have been developed, it is still a very challenging task to design a robust and efficient algorithm to segment (noisy, blurred or even discontinuous edged) images having high intensity inhomogeneity or non-homogeneity. In this article, a robust fuzzy energy based active contour, using both global and local information, is proposed to detect objects in a given image based on curve evolution. The local energy is generated by considering both local spatial and gray level/color information. The proposed model can better deal with images having high intensity inhomogeneity or non-homogeneity, noise and blurred boundary or discontinuous edges by incorporating local energy term in the proposed active contour energy function. The global energy term is used to avoid unsatisfactory results due to bad initialization. In this article, instead of solving the Euler–Lagrange equation, a level set based optimization is used for the convergence. We show a realization of the proposed method and demonstrate its performance (both qualitatively and quantitatively) with respect to state-of-the-art techniques on several images having such kind of artifacts. Analysis of results concludes that the proposed method can detect objects from given images in a better way than the existing ones.

1. Introduction

Image segmentation, a fundamental task in the field of image processing has been widely applied in computer vision, image analysis, medical imaging, etc. [1]. It is a process of dividing a given image into several parts, each is homogeneous with respect to some features like intensity, color, texture [1,2]. In literature, several techniques have been developed for segmenting images. However, the design of robust and efficient segmentation algorithms is still a very challenging and important task due to the complexity present in the images.

A large number of image segmentation techniques has been proposed in the literature. Among them, clustering based methods and active contour models (ACM) are quite popular. In this direction, various clustering based methods [3–6] have been introduced for segmenting images. Among them, one of the most popular techniques for image segmentation is fuzzy clustering [6]. It introduces the degree of belongingness of each image pixel and can retain more information from the original image than hard clustering [4]. However, it does not consider any spatial information in the image context, which makes it very sensitive to noise, outliers and other artifacts. Several modifications of fuzzy clustering [7–9] have been done by incorporating local information derived from the image to increase the accuracy of image segmentation.

On the other hand ACMs are successfully applied for image segmentation [10], object detection and tracking [11,12], feature extraction [13], image registration [14], etc. Kass et al. [11] introduced the active contour (snake) model to detect and track object. The main idea behind the ACM is based on deformation of an initial curve so that it evolves toward the object boundary under some constraints. It has the ability to generate closed parametric curve [15]. However, it has some drawbacks such as: (i) segmentation results highly depend on initial contour position, (ii) it is easily deteriorated by noise present in the given image. Several approaches [16–25] based on ACMs have been developed to overcome such drawbacks to some extend.

Caselles et al. [16] proposed a geometric active contour model based on curve evolution. In this method, the curve is evolved in

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the direction of normal force and stopped at the object boundary using energy based function. In [17], geometric active contour was implemented using level set methods. In these approaches, the topology can be changed to capture multiple objects without additional effects. However, these methods can not work well for images having poor contrast between the objects and the background. To cope with such limitations, geodesic active contour [18,19] was introduced to segment such kind of images. It is basically a problem of finding minimal distance curves in a Riemannian space [18,19]. The energy function is similar to the snake model. On the other hand, Cohen and Kimmel [20] proposed a minimal path technique to obtain global minimum contour energy between two user defined end points. In [21], active contour model using level set is proposed to segment images. Level set evolution is derived as the gradient flow that minimizes an energy function with a distance regularization term and an external energy that drives the motion of the zero level set toward the desired locations. Some other models like dual snakes [22] and dual band active contour [23] were developed to find the boundary of an object in the literature.

All the above discussed active contour and its variants are basically "edge based" models which use image gradient to attract the contour toward object boundaries. As these models rely on edge information, sometime it may fail to extract contour when gradient of the object boundaries is not well defined for noisy, blurred or even discontinuous edged images.

Different from "edge based" active contours, a "region based" active contour models [26–42] using region information like intensity, color and texture features are introduced in the literature. In general, the "region based" models use image information from not only the evolving contour but also from image statistics inside and outside the contour. Chan and Vese [27] proposed an active contour (Chan–Vese) model which depends on the region based energy function, inspired by Mumford–Shush function [43]. In this model, two regions inside and outside the contour in the image are assumed to be homogeneous. Here, global image (statistics) information is used in the energy function and transforms it into the level set formulation. The Chan–Vese model as well as other region based models are able to deal with images having weak boundaries. In addition, they are less sensitive to the initial contour position as compared to the "edge based" model.

Some modifications in the Chan–Vese model have been done in literature [28,29,31–34,44] mainly to reduce the high computational cost of this model. In [31], Krinidis and Chatzis proposed a "region based" active contour model to segment images. This model uses global image information which is able to segment images with blur and discontinuous boundary and is robust to the initial position of the contour. In this model, they assumed that the image is approximated with two regions of the piece-wise constant intensities inside and outside the contour. However, this model is unable to produce good segmentation for images containing intensity inhomogeneity or non-homogeneity.

In fact, real life images contain intensity inhomogeneity or non-homogeneity which makes the segmentation a more challenging problem. To segment such kind of images, region based active contours using local image (statistics) information are proposed in the literature [28,29,32–34]. In [28], a region-based active contour model is proposed using intensity information in local regions at a controllable scale. Lankton and Tannenbaum [29] proposed region based active contour using local image statistics and the energy function is reformulated based on local information. It is able to segment heterogeneous images. In [33], Zhang et al. also developed new region based active contour using local image statistics. Local image statistics is extracted using local image fitting energy. Here, Gaussian filtering for variational level set is proposed [33] to regularize the level set function. Zhang et al. [34] proposed a novel region-based active contour model using Selective Binary and Gaussian Filtering regularized level set. The main drawback of these models is that results highly depend on the initial contour position. Energy function of these models are transformed into level set formulation and minimized by solving the corresponding Euler–Lagrange equations which is slow to converse. To reduce the high computational cost of Chan–Vese model and its variants, online region-based active contour model is proposed in [44]. This model used binary level set and new regularization operation such as morphological opening and closing to reduce execution time. It is free from any parameter. However, all these models are unable to produce good results for highly noisy and intensity inhomogeneity images.

To overcome such drawbacks, "region based" active contours using both global and local information are developed in the literature [45,46]. In both these methods, local information, based on only the spatial distance is considered and they are not robust to high level of noise, hybrid noise and intensity inhomogeneity or non-homogeneity present in the images.

In this article, a robust fuzzy energy based active contour using both global and local information is proposed to segment (noisy and blurred) images with high intensity inhomogeneity or non-homogeneity. The local information is generated based on both the spatial distance and the pixel intensity. The proposed model can deal with images having high intensity inhomogeneity or non-homogeneity as well as noise by incorporating local information into the energy function. Here, the global information in the energy function is used to avoid unsatisfactory results due to bad initialization. The local information in the energy function is considered to deal with noise and high intensity inhomogeneity present in the given image. Fuzzy energy is calculated directly by zero level set based optimization technique as considered in [31,46], instead of solving the Euler–Lagrange equations.

To test the effectiveness of the proposed algorithm, investigation was carried out on twenty two images having intensity inhomogeneity or non-homogeneity. Segmentation results of the proposed method are compared with those of seven state-of-the-art segmentation algorithms. Three existing evaluation measures are used to evaluate the performance of the proposed algorithm. *t*-Test is also considered to establish the statistical significance of the proposed segmentation algorithm. From the analysis (both quantitative and qualitative) of results and *t*-test, it is found that the proposed method performs favorably against state-of-the-art techniques. In particular, the proposed algorithm is able to segment noisy, blurred images containing high intensity inhomogeneity.

Rest of the article is organized as follows. Section 2 briefly describes the proposed global and local fuzzy energy based active contour for image segmentation. Experimental results and analysis are presented in Section 3. Section 4 discusses about the parameters and some issues for the performance of the proposed technique and finally conclusive remarks are put in Section 5.

2. Proposed model

In this section, we propose a fuzzy energy based function that takes both the global and local information. Let a given vector valued image be $I(X) : \Omega \to \mathfrak{R}^d$, where $\Omega \subset \mathfrak{R}^2$ is the image domain and $d \geq 1$ is the dimension of the vector $I(X)$. In particular, $d = 1$ for gray level images while $d = 3$ for color images. Let C be a closed contour in the image domain Ω which separates Ω into two regions: $\Omega_1 = inside(C)$ and $\Omega_2 = outside(C)$. The general form of the proposed