Optik 125 (2014) 5257–5263

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Arbitrary initialization for Chan–Vese model

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ARTICLE INFO

Article history:
Received 21 September 2013
Accepted 15 May 2014

Keywords:
Image segmentation
Active contours
Initialization
Chan–Vese model
Examination criterion

ABSTRACT

Three problems about initialization of Chan–Vese model impeding its applications of Chan–Vese model, are discussed in this paper first by various experiments. Then, a novel method to solve these badly initialization problems is proposed, which can be divided into three parts: a hypothesis that image boundaries do not contain any feature of the objects; an examination criterion to check whether the current contour is suitable for continuing or not; and a method to revise the unsuitable current contour into a new one. The most important advantage of our proposed method is that it realizes the arbitrary initialization which can release the manual work in essence. Extensive experiments on synthetic and real images demonstrate the advantages of the proposed method.

1. Introduction

Image segmentation is the process of partitioning an image into regions with different properties, for example, in each of which the intensity is homogeneous. Its goal is to change the representation of an image into something that is easier to understand, analyze or recognize for people or even machines. Image segmentation has always been a fundamental problem and complex task in the field of image processing and computer vision. Up to now, a large body of methods has been proposed to solve the image segmentation problem. Active contours is one of the famous methods which can be divided into two kinds: edge-based methods such as the classical snakes [1] and geodesic active contours [2], and region-based methods such as Chan–Vese model [3]. The edge-based methods drive the initial contour to the boundaries of objects in the image based on gradient information. The well known edge-based method snakes, proposed by Kass [1] in 1988, has been proved to be a sufficiently powerful and robust framework for image segmentation. As these methods use series of parameters to describe the contours, so we call these edge-based methods parametric active contour models. Much of the early work done in active contours was by using parametric representations of the contours. A limitation of parametric models is that it has difficulty in dealing with topological adaptation such as splitting or merging model parts. In the recently popularized geometric approach, level set method that evolves a higher dimensional function whose zero-level set always corresponds to the position of the propagating contour, is often considered to be superior to parametric active contours, to a large extent because of its ability to handle merging or splitting of the evolving contour and its numerical stability of the solution. A particularly appealing method of this type is the model of "active contours without edges" proposed by Chan and Vese, based on the well-known Mumford–Shah functional [4] for image segmentation. As this method is not based on edges, it can detect the objects with week or blurred edges effectively, on which the edge-based models such as snakes or geodesic active contours may fail. However, Chan–Vese model also has its limitations. First, this model is usually implemented by solving partial differential equations, and is thus computationally intense. Second, this model sometimes has initialization problems.

Initialization is a thorny problem not only in region-based models such as Chan–Vese but also in the edge-based parametric models. As the region-based models are superior to the edge-based models in some aspects, we concentrate on the initialization problem of Chan–Vese model, which is a representative of the region-based models. Researchers have already made some contribution to the initialization problem of Chan–Vese model. Vemuri and Chen [5] proposed a variation level set formulation which is able to perform joint image registration and segmentation by incorporating shape-prior information. And Huang [6] also added the shape knowledge into the Chan–Vese segmentation method, and showed that the segmentation results of the proposed method are better on some specific images. However, the shape knowledge involved in the above two methods should be added by users, which means that their methods may work manually. Xia et al. [7] proposed an initialization scheme for improving the

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http://dx.doi.org/10.1016/j.ijleo.2014.06.051
0030-4026/

segmentation performance of Chan–Vese model. It consists of two stages: computes the rough edges by using Canny edge detection operator firstly; and removes noise edges by morphological filter, then generates closed contours by iteratively connecting edge points according to a local cost function secondly. However, canny operator is determined by three parameters: Gaussian standard deviation, the upper threshold and the lower threshold. What is more, the structuring element is needed when we use morphological filter, and the shape and size of the structuring element determine the performance of morphological filter. So there are at least five parameters to be known to implement [7]. The above methods are all image preprocessing methods, which are violating the principle that the good initial contours should be found automatically in order to minimize user intervention. Another kind of methods may be called re-initialization, which is done during the process of contour evolving. Unfortunately, many existing re-initialization methods [2,8,9] have an undesirable side effect of moving the zero level set away from its interface. Furthermore, it is difficult to decide when and how to apply the re-initialization. Contrary to the re-initialization methods, some researchers propose some schemes which can avoid re-initialization. Zhang et al. [10] proposed a method driven by local image fitting energy, which can eliminate the requirement of re-initialization. And Li et al. [11] proposed a variation level set formulation that forces the level set function to be close to a signed distance function, and therefore eliminates the need of the costly re-initialization procedure. As pointed by [12], re-initialization is a very expensive operation. Therefore, methods which can solve the problem of initialization may be the solutions to eliminate the re-initialization procedure.

After large amounts of experiments, we have discovered three problems about initialization of Chan–Vese model: when the initial contour is not suitable, i.e., the initial contour is located far away from the objects we are interested in, the segmentation result may be just the supplementary set of our object; unsuitable initial contour may cover less information about the object than the suitable initial contour, which can not achieve the aim image segmentation; and it costs more time to end the evolution. If the image to be segmented is really simple, the supplementary set of our object can also be transformed into the object part easily. Unfortunately, if it is very complex, this transform may not work so well. When the initial contour is not suitable, the segmented results MR of breast or brain, which are usually used in clinical diagnosis, may provide less information about breast or brain, which may lead to the inaccurate diagnosis. As for the speed of evolution, users always hope it to be as short as possible. These problems may be solved by users to locate the initial contour more closer to the object, however, this manual method restrict the Chan–Vese model's application in automatically detection.

In this paper, we propose a simple method to solve the problems of initialization. It is based on Chan–Vese model and a hypothesis that the boundaries of the input image do not contain any feature of the object. We implement the Chan–Vese model and examine whether the current contour touches the boundaries of the input image during iterations. If it does, we may consider that this initial contour is unsuitable, and we make use of the information of the current contour to locate a new contour. As our method is based on Chan–Vese model and the examination criterion to locate a new contour, the initial contour can be far away from the object in the image, which overcomes the initialization problems of Chan–Vese model perfectly.

The outline of this paper is as follows. In Section 2, a brief review of the famous Chan–Vese model is given, and the three important problems with Chan–Vese model about initialization by some experiments are demonstrated. In Section 3, we explain in detail our method to solve the problems discussed in Section 2. And our proposed method can be divided into three small parts: a hypothesis; a checking criterion; and a simple method to locate a new contour based on the current contour information. In Section 4, we validate the proposed method by various numerical results on synthetic and real images, showing the advantages of our method described in Section 3. We end the paper by a concluding section.

2. The initialization problems of Chan–Vese model

Initialization is not the problems of edge-based models but also of region-based models. In this paper, we only concentrate on the initialization problem of Chan–Vese model. Firstly, let us review the famous Chan–Vese model briefly. Then, we will show the initialization problems with it by some experiments both on synthetic and real images.

2.1. The Chan–Vese model

In this section, we briefly recall the Chan–Vese model. Chan and Vese [3] proposed a famous region-based model based on Mumford-Shah functional [4] for image segmentation, and it is a simplified version of [4]. Let I be the image to be detected, with ∂I its boundaries, C be the initial or current contour. Chan–Vese model minimizes THE energy as follows:

$$E^{CV}(c_1, c_2, C) = \mu L(C) + \nu A(C) + \lambda_1 \int_{\text{inside}(C)} \left| I - c_1 \right|^2 dxdy + \lambda_2 \int_{\text{outside}(C)} \left| I - c_2 \right|^2 dxdy \quad (1)$$

where c_1 is the average intensity inside C and respectively c_2 is the average intensity outside C; $L(C)$ is the length of C, and $A(C)$ is the area inside C.

Introducing level set method [13], Heaviside function H and the one dimensional Dirac measure δ_0, the energy $E^{CV}(c_1, c_2, C)$ can be written as

$$E^{CV}(c_1, c_2, \phi) = \mu \int_I \delta(\phi(x,y)) \left| \nabla\phi(x,y) \right| dxdy + \nu \int_I H(\phi(x,y))dxdy + \lambda_1 \int_I \left| I(x,y) - c_1 \right|^2 H(\phi(x,y))dxdy + \lambda_2 \int_I \left| I(x,y) - c_2 \right|^2 H(\phi(x,y))dxdy \quad (2)$$

where, $\begin{cases} C = \{(x,y) | \phi(x,y) = 0\} \\ \text{inside}(C) = \{(x,y) | \phi(x,y) > 0\} \\ \text{outside}(C) = \{(x,y) | \phi(x,y) < 0\} \end{cases}$, $H(z) = \begin{cases} 1, z \geq 0 \\ 0, z < 0 \end{cases}$, $\delta_0 = dH(z)/dz$.

Solving Eq. (2) contains two steps. First, keep ϕ fixed and minimize the energy $E^{CV}(c_1, c_2, \phi)$ with respect to c_1 and c_2, and we obtain

$$c_1(\phi) = \int_I I(x,y)H(\phi(x,y))dxdy \Big/ \int_I H(\phi(x,y))dxdy, \quad c_2(\phi) = \int_I I(x,y)(1 - H(\phi(x,y)))dxdy \Big/ \int_I (1 - H(\phi(x,y)))dxdy. \quad (3)$$

Second, fix c_1 and c_2, and minimize the energy $E^{CV}(c_1, c_2, \phi)$ with respect to ϕ, and we get

$$\frac{\partial\phi}{\partial t} = \delta(t) \left[\mu div \left(\nabla\phi / \left| \nabla\phi \right| \right) - \nu - \lambda_1 (I - c_1)^2 + \lambda_2 (I - c_2)^2 \right]. \quad (4)$$

As the images we use are all digital images, therefore we have to discrete Eqs. (3) and (4). The discrete version of Eq. (3) is

$$c_1(\phi) = \sum_I \sum_I I(x,y)H(\phi(x,y)) \Big/ \sum_I \sum_I H(\phi(x,y)), \quad c_2(\phi) = \sum_I \sum_I I(x,y)(1 - H(\phi(x,y))) \Big/ \sum_I \sum_I (1 - H(\phi(x,y))) \quad (5)$$