Engineering Applications of Artificial Intelligence 35 (2014) 199–214

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Robust medical image segmentation using particle swarm optimization aided level set based global fitting energy active contour approach

Devraj Mandal, Amitava Chatterjee*, Madhubanti Maitra

Electrical Engineering Department, Jadavpur University, Kolkata 700032, India

ARTICLE INFO

Article history:
Received 26 February 2014
Received in revised form
22 April 2014
Accepted 1 July 2014
Available online 23 July 2014

Keywords:
Active contours
Energy minimization
Particle swarm optimization
Segmentation

ABSTRACT

The active contour models have been popularly employed for image segmentation for almost a decade now. Among these active contour models, the level set based Chan and Vese algorithm is a popular region-based model that inherently utilizes intensity homogeneity in each region under consideration. However, the Chan and Vese model often suffers from the possibility of getting trapped in a local minimum, if the contour is not properly initialized. This problem assumes greater importance in the context of medical images where the intensity variations may assume large varieties of local and global profiles. In this work we propose a robust version of the Chan and Vese algorithm which is expected to achieve satisfactory segmentation performance, irrespective of the initial choice of the contour. This work formulates the fitting energy minimization problem to be solved using a metaheuristic optimization algorithm and makes a successful implementation of our algorithm using particle swarm optimization (PSO) technique. Our algorithm has been developed for two-phase level set implementation of the Chan and Vese model and it has been successfully utilized for both scalar-valued and vector-valued images. Extensive experimentations utilizing different varieties of medical images demonstrate how our proposed method could significantly improve upon the quality of segmentation performance achieved by Chan and Vese algorithm with varied initializations of contours.

1. Introduction

Active contour models (Kass et al., 1988; Caselles et al., 1993, 1997) also called snakes are used for detecting an object outline from an image. Very often the active contour models employ energy based segmentation techniques (Chan and Vese, 2001), where the basic idea is to minimize the energy associated with the active contour, as the curve evolves to fit around the desired objects. The energy associated with an active contour generally consists of internal energy and external energy. The internal energy deals with the properties of the contour such as area enclosed, length of the contour and its smoothness. The external energy depends upon the image structure and the user imposed constraints.

Let Ω be a bounded open subset of $\Re^2$ and $\partial\Omega$ be its boundary. Let u_0 be the given image and C be the contour under consideration. The objective is to evolve the curve C, such that the energy associated with it progressively decreases and becomes minimum when the curve fits exactly on the desired objects of interest. Let the curve C be parameterized as $C(s):[0,1]\rightarrow\Re^2$. Then the energy associated with it is given as (Chan and Vese, 2001)

$$J_1(C)=\alpha\int_0^1 \left|C^{'}(s)\right|^2 ds+\beta\int_0^1 \left|C^{''}(s)\right| ds-\lambda\int_0^1 \left|\nabla u_0(C(s))\right|^2 ds \quad (1)$$

here α, β and γ are positive parameters (Kass et al., 1988). The first order term forces the contour to act like a membrane. The second term makes the contour act like a thin plate. These two terms together contribute to the elastic energy and the bending energy of the snake and forces it to be smooth. The third term consists of the image forces that help the snakes to get attracted towards the salient features of the images. Different types of image forces such as line functional, edge functional and scalar spaces have been defined (Kass et al., 1988), although edge functionals are mostly used.

The classical snake model in Kass et al. (1988) considered the minimization of the energy functional in (1). The main problem with this method was that the evolving contour that was defined parametrically, could not detect cusps, corners and automatic topological changes. This problem was later solved by the use of level sets (Osher and Sethian, 1988). The level set formulation helped in detecting interior contours, cusps, multi-junctions etc. and it could automatically handle topological changes. Level set method was quite different from the conventional Eulerian approach in which parameterization was required to track contours and surfaces.

Traditionally, an edge-detector such as $E_{edge}=-|\nabla u_0(x,y)|^2$ (Kass et al., 1988) is being used to stop the evolving contour on the boundary of the object to be detected, where (x,y) denotes the coordinates in the rectangular grid domain of the image u_0. It is well known that an edge-detector relies on the image gradient information. The edge-detectors can only detect objects within an

* Corresponding author.
E-mail address: cha_ami@yahoo.co.in (A. Chatterjee).

http://dx.doi.org/10.1016/j.engappai.2014.07.001
0952-1976/

image which are strongly defined by its image gradient function. In case, the image contains weakly defined edges, the edge-detector function will not be able to stop the curve evolution at these points. Also, if the image is very noisy or blurred, the edges get smoothened and the edge-detector fails in these cases too. Sometimes, before image segmentation, Gaussian filtering is used as a pre-processing step which may blur the edges of the image. In these cases too, the edge-detector function is not a suitable choice (Caselles et al., 1993; Malladi et al., 1995, 1993).

Due to the poor performances of these initially developed edge-based models, region-based models were later independently developed by Chan and Vese (2001) and Tsai et al. (2001) which became quite popular. Instead of identifying objects through its edges, region-based models use certain region particulars to evolve the contour towards them. The Chan and Vese model was developed for both the piecewise constant case (Chan and Vese, 2001) and the piecewise smooth case (Vese and Chan, 2002). The piecewise constant model could only deal with images having homogenous regions while the piecewise smooth model could deal with images having intensity inhomogeneity. These works carried out by Chan and Vese utilized level sets to evolve the contour. They exhibited considerable improvements over the edge-based models due to the fact that interior contours could be efficiently detected and hence the Chan and Vese algorithms could be used for images with weak boundaries.

One of the problems associated with the Chan and Vese model was that the fitting energy functional (Chan and Vese, 2001) defined, was non-convex and non-unique in nature. Hence, often it got stuck in local minima during curve evolution and hence could not achieve the desired segmentation result. In Brown et al. (2012), this problem has been addressed and the authors have attempted to convert the Chan and Vese energy functional into a convex formulation. However, generally speaking, the performance of the Chan and Vese model is known to be quite sensitive to the initial choice of the contour. Often, if the contour is initialized far away from its final solution, this level set based method is unable to evolve the curves to approach the final global solution. The present work addresses this basic weakness of the Chan and Vese algorithm and proposes a robust solution for it which is insensitive to the initial choice of contour. This work proposes to solve the problem by using a metaheuristic optimization based solution. These metaheuristic based or swarm intelligence based optimization procedures are mostly population based methods that are known as non-gradient type optimization algorithms which can efficiently achieve the global optimum or the sub-optimum avoiding the local minima of a solution. These metaheuristic optimization algorithms are increasingly employed to solve various categories of image processing problems, e.g. image segmentation, image compression, image retrieval, image classification etc. (Chatterjee and Siarry, 2013; Chatterjee et al., 2012, 2013; Sanyal et al., 2011; Maitra and Chatterjee, 2008a). The present work first formulates the problem at hand as a metaheuristic optimization problem and then solves it by using particle swarm optimization (PSO) algorithm, a very popular technique in the genre of metaheuristic optimization (Kennedy and Eberhart, 1995; Shi and Eberhart, 1998). The proposed algorithm has been extensively implemented for medical image segmentation and its performance has been evaluated vis-à-vis Chan and Vese algorithm, to demonstrate the usefulness of our proposed method.

The outline of this paper is as follows: In Section 2 we describe the Chan and Vese model for the piecewise constant case in detail for both the scalar and the vector-valued cases. A detailed account of the advantages and disadvantages of this model are also presented. In Section 3 we describe the basic PSO algorithm and, subsequently, our proposed formulation of the PSO based robust Chan and Vese Model for image segmentation using level sets. In Section 4, we implement our model for various gray-scale and color medical images and perform a detailed performance analysis. Section 5 presents the conclusion.

2. The Chan and Vese model (piecewise constant model) for image segmentation

As mentioned before, Chan and Vese (2001) proposed a piecewise-constant model for image segmentation. An evolving curve C in Ω, is defined as the boundary of an open subset ω of Ω (i.e. $\omega \subset \Omega$, and $C = \partial\omega$). Then $inside(C)$ denotes the region ω, and $outside(C)$ denotes the region $\Omega/\overline{\omega}$ (Chan and Vese, 2001). The image u_0 is assumed to be formed by two regions of piecewise-constant intensities having distinct values u_0^i and u_0^o. u_0^i represents the intensity of the object to be detected and u_0^o the intensity of the background of the object. The object is assumed to have a boundary or bounding contour C_0. Then the intensity inside C_0 is u_0^i and the intensity outside C_0 is u_0^o. Thus the energy fitting term can be defined as (Chan and Vese, 2001)

$$\begin{aligned} F(c_1, c_2, C) = {} & \nu.Length(C) + \mu.Area(inside(C)) \\ & + \lambda_1 \int_{inside(C)} |u_0(x,y) - c_1|^2 dxdy \\ & + \lambda_2 \int_{outside(C)} |u_0(x,y) - c_2|^2 dxdy \end{aligned} \tag{2}$$

where C is any curve that is being iteratively evolved, and the constants c_1 and c_2 denote the average intensity of the image inside and outside the evolving curve C. The free parameters of the equation in (2) must all be positive. The fitting energy (2) also contains some penalizing terms such as the length of the evolving curve C and the area of the region inside the curve C. These two terms helps to smoothen the evolving contour C. It is quite evident from the above Eq. (2) that the energy associated with the contour C becomes minimum when $C \approx C_0$ i.e., the evolving contour sits exactly on the object boundary.

The above functional in (2) is quite similar to that as the Mumford–Shah Functional (Mumford and Shah, 1989). The Mumford–Shah Functional (F^{MS}) tries to segment an image into its various sub-regions by using region-based information. The Chan and Vese model tries to represent each region or connected component R_i of Ω/C using a constant intensity c_i. This c_i represents the average intensity of the region i.e. $c_i = average(u_0)$ on each connected component R_i (Chan and Vese, 2001; Mumford and Shah, 1989). This reduced case is called the minimal partition problem. Here the values of the constants are

$$\begin{aligned} c_1 &= mean(inside(C)) \\ c_2 &= mean(outside(C)). \end{aligned} \tag{3}$$

2.1. Level set formulation of the model

In level set methods (Chan and Vese, 2001; Osher and Sethian, 1988), a contour $C \subset \Omega$ is represented by the zero level set of a Lipschitz function $\phi : \Omega \to R$. This is also called a level set function and it is defined in such a way that

$$\begin{cases} C = \partial\omega = \{(x,y) \in \Omega : \phi(x,y) = 0\} \\ inside(C) = \omega = \{(x,y) \in \Omega : \phi(x,y) > 0\} \\ outside(C) = \Omega/\overline{\omega} = \{(x,y) \in \Omega : (x,y) < 0\} \end{cases} \tag{4}$$

Using the level set function ϕ and also the Heaviside function H and the one-dimensional Dirac measure δ_0 so as to use one-dimensional calculations, the energy fitting terms $F(c_1, c_2, C)$ can