Signal Processing 108 (2015) 147–158

Contents lists available at ScienceDirect

Signal Processing

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

A hybrid active contour model with structured feature for image segmentation

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ARTICLE INFO

Article history:
Received 22 February 2014
Received in revised form
28 May 2014
Accepted 6 September 2014
Available online 16 September 2014

Keywords:
Active contour model
Image segmentation
Anisotropic data fitting term
Structured gradient vector flow
Duality formulation

ABSTRACT

We propose a structural feature region-based active contour model based on the level set method for image segmentation. Firstly, an anisotropic data fitting term is proposed to adaptively detect the intensity both in terms of local direction and global region. Secondly, coupling with the duality theory and a structured gradient vector flow (SGVF) method, a new regularization term of the level set function is formulated to penalize the length of active contour. By this new regularization term, the structured information of images is utilized to improve the ability of preserving the elongated structures. The energy function of the proposed model is minimized by an efficient dual algorithm, avoiding the instability and the non-differentiability of traditional numerical solutions. We compare the proposed method to classical region-based active contour models and highlight its advantages through experiments on synthetic and medical images.

1. Introduction

Active contour models have been widely used in image processing and computer vision applications, especially in image segmentations. Depending on how object boundary is detected, active contour models can be categorized into parameterized [1–5] and non-parameterized models [6–17]. The typical parameterized models assume that the prior information of the object boundary is available, which is not always realistic. Hence, the shortcomings of these parameterized models usually include initialization sensitivity and failure to converge to concavities. To avoid this drawback, the external forces, e.g., the balloon force proposed as in [2] are introduced. The gradient vector flow (GVF) method [4,5] is one of the most effective parameterized active contours models. It extends the gradient force near the edges to the whole image so that the deformation of the active contour is more flexible and the deformation scope of the active contour is extended to the whole image. Nevertheless, it also has some disadvantages, such as expensive computational load, the ambiguous relationship between the capture and parameters. Non-parameterized models have some advantages over parameterized models. Firstly, by using non-parameterized models, the object boundary detection based on the image gradient is not affected by noise and weak edges. Secondly, they are also significantly less sensitive to initialization. By using the Mumford–Shah functional [18] for segmentation, the Chan–Vese (CV) model [6] extracts object boundary with intensity information in a global region but not with the gradient information. This model assumes that each image region is statistically homogeneous. It has been successfully used in the binary phase segmentation, which is implemented through the level set method [19]. The CV model has motivated many other non-parameterized active contour models [7–12,15–17,21,22,29] as well.

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http://dx.doi.org/10.1016/j.sigpro.2014.09.007
0165-1684/

Medical images including magnetic resonance images (MRI) contain several anatomical structures. Accurate segmentation of one object is quite important for diagnosis and therapeutic interventional planning. Generally, some common features in medical images, such as low-contrast object boundaries, elongated structures, and the intensity un-uniformity, make it more challenging to segment the target objects than other applications. Hence, it is widely investigated in the research field. In literatures [7–12] local statistical information is embedded into a non-parameterized active contour model in order to overcome intensity un-uniformity (the intensities in the same sub-region vary spatially) and noise. However, the intensities in an image vary spatially and so does intensity un-uniformity. The fixed-scale estimation method for calculating the local statistical information in [7–12] may lead to imprecise results. Additionally, the active contours based on region statistical information, including global and local ones, are both lack of structure information to extract elongated structures.

In this paper, we propose an anisotropic data fitting term that differentiates the sub-regions according to local intensity information along the active contour and the global intensity information adaptively. When a contour is close to object boundaries, the anisotropic fitting term mainly detects the local intensity information near the contour; whereas when there is no obvious intensity variation near the contour, it mainly detects the global intensity information. This new data fitting term focuses on calculating the intensities near the active contours along the local directions where the intensity changes notably. On the other hand, it calculates the global intensity information when a region is flat, i.e., there is no obvious intensity variation. Hence, the anisotropic data fitting term extracts the local information only when there is intensity non-uniformity, while it accelerates the contour evolution with the global intensity information. Particularly, we introduce a new regularization term coupling with a structured gradient vector flow model. With this new regularization term, structured information is extracted by minimizing the energy functional of structured gradient vector flow with respect to the dual variable of the level set function. Experiments on synthetic and medical images show that the active contour captures more elongated structures effectively. The proposed model is solved through a split dual formulation of the global minimization problem [15] to avoid the instability and the un-differentiability issues induced by traditional gradient descent method.

This paper is organized as follows. The previous work is reviewed in Section 2. Then the proposed model and algorithm are described in Section 3. Section 4 shows the experiment and results of the proposed method. Finally a brief conclusion comes in Section 5.

2. Previous work

2.1. The global convex segmentation model

In order to overcome the local optimizer of the evolution process and the topology problem caused by the parameterized active contour model [4], Caselles et al. [3] proposed Geodesic Active Contour model (GAC). In a continuous formulation, the GAC model is equivalent to the weighted total variation (TV) as shown by Bresson et al. [15]. Combined this weighted TV with the global convex energy functional of the CV model (GCV) [13], the global convex segmentation model (GCS) [14,15] is defined as follows:

$$\min_{0<\phi<1} \int_\Omega g_b |\nabla\phi|\, dx + \mu \int_\Omega \left((I-c_1)^2 - (I-c_2)^2 \right) \phi\, dx, \tag{1}$$

where Ω represents the image domain, $I(x)$: $\Omega \to R$ is an input image, $\phi(x)$ represents the level set function, μ represents the positive parameter, g_b is an edge gradient indicator. It is close to 0 near a strong edge; otherwise, it is close to 1. In [14,15], it is given as $g_b = (1/(1+|\nabla I|^2))$. The region fitting term $\mu \int_\Omega ((I-c_1)^2 - (I-c_2)^2)\phi\, dx$ drives the contour during evolution. We denote by Ω_1 and Ω_2 as regions inside and outside the contour C, respectively. Once this minimization problem is solved, i.e. the minimizer of ϕ is solved, the two regions inside and outside the contour are determined by a thresholding $\alpha \in (0,1)$:

$$\Omega_1 = \{x: \phi(x) > \alpha\}, \quad \Omega_2 = \{x: \phi(x) < \alpha\}. \tag{2}$$

Then the intensity averages of the two regions are updated as follows, respectively,

$$c_1 = \frac{\int_{\Omega_1} I(x) dx}{\int_{\Omega_1} dx}, \quad c_2 = \frac{\int_{\Omega_2} I(x) dx}{\int_{\Omega_2} dx} \tag{3}$$

The experimental results in [15] have shown that the GCS model is robust to the initial condition because the GCS model has a global minimizer, and it has the advantage of capturing the weak boundaries comparing to the CV model. In the CV model and the GCS model, c_1 and c_2 are related to the global statistical information of the image contents inside and outside the contour, respectively. Such global image information is not the real statistical information of the image intensity, if the intensity inside or outside the contour is un-uniformity. In order to overcome this limitation, Li et al. [7] embedded local intensity information into the region-based active contour model. However, this method and the related methods [7–12,16,22] utilize a fixed-scale estimation method to calculate the local intensity statistics, which may cause undesirable results and the fixed parameters should be properly chosen according to the images.

2.2. GVF: gradient vector flow for active contours

In the seminal work of the snake model by Kass et al. [1], the active contour is deformed by internal and external forces. Typically the internal force makes the snake contour smooth while the external force is defined as the gradient vector of the image edge map. A major drawback of this gradient vector is the local nature of the evolution process, which is more likely to get stuck in local minima. Xu and Prince [4,5] replaced the external force with a new vector field with a general form in [5]. This vector field is derived by minimizing a certain energy functional in the variational framework:

$$E_{GVF} = \iint \mu \left(u_x^2 + u_y^2 + v_x^2 + v_y^2 \right) + |\nabla f|^2 |\mathbf{w} - \nabla f|^2 dx\, dy, \tag{4}$$