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A novel snake model using new multi-step decision model for complex image segmentation

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ABSTRACT

Active contours, or snakes, have a wide range of applications in object segmentation, which use an energy minimizing spline to extract objects' borders. Classical snakes have several drawbacks, such as the initial contour sensitivity and convergence ability to local minima. Many approaches based on active contours are put forward to addressing these problems. However, these approaches have limitation that they all depend too much on the amplitude of edge gradient and abandon directional information. This can lead to poor convergence toward the object boundary in the presence of strong background edges and cluttered noises. To deal with these issues, we first propose a novel external force, called adaptive edge preserving generalized gradient vector flow based on component-based normalization (CN-AEGGVF), which can adaptively adjust the process of diffusion according to the local characteristics of an image and preserve weak edges by adding the gradient information of an image. The experimental results show that the new model provides much better results than other approaches in terms of noise robustness, weak edge preserving, and convergence. Secondly, an improved multi-step decision model based on CN-AEGGVF is presented, which added new effective weighting function to attenuate the magnitudes of unwanted edges and adopted narrow band method to reduce time complexity. The novel method is analyzed visually and qualitatively on nature image dataset. Experimental results and comparisons against other methods show that the proposed method has better segmentation accuracy than other comparative approaches.

1. Introduction

Active contour model, or snake model, was proposed by Kass et al. [1] in 1987. Snake model has been widely used in the fields of computer vision and image processing, for instance, edge detection [2,3], image segmentation [4,5], and target tracking [6,7]. Snake is an elastic curve which captures the target area of an image by minimizing an energy equation. The energy function generally contains an internal force field and an external force field.

The internal force field, determined by the curve itself, is used to restrain the smoothness and tightness of snake curve. The external force field has the function to drive evolving curve to approach the edge of interesting features in an image. Overall, active contour models are divided into parameter snake model and geometric snake model, whereas the former one is the subject in this paper.

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Although conventional active contour model has been widely used, it still has certain disadvantages [8,9]. First, the initial contour must be very close to the interesting features in an image, because the external force field recedes rapidly when the curve is far away from the image edges. Second, image noises may stop the deformation of active contour where the local minimum energy is obtained and leads the contour to incorrect border. The disadvantages limit the applications of original active contour model, which can only handle the objects without cluttered background while the initial active contours are not far from the edges.

Xu proposed GVF snake model [10] based on a new external force field, called gradient vector flow (GVF), which is able to expand the capturing scope of initial contour and has certain convergence capability of indentation. GVF has been widely used and adapted to various models and problems, e.g., segmentation [11], tracking [7], registration [12], and skeletonization [13]. However, during the diffusion of external force field, the competing of forces happens. Thus, the GVF has the difficulty in driving a snake into long and thin indentations as well as noise sensitivity.

Based on the original GVF external force field, Xu and Prince replaced the constant weighting coefficient with two spatially varying weighting functions, and put forward the generalized gradient vector flow (GGVF) snake model [14]. The GGVF has improved GVF convergence to LTIs as well as robustness to noises. However, there is no essential difference between GGVF and GVF, so the ability of entering into the concavity of edge is limited. NGVF snake model proposed by Ning [15] decomposes the Laplace operator in the GVF external force field, and only retains the normal component [16], in this way, it can enter into LTIs at a faster convergence speed. Nevertheless, diffusion along the tangent direction is beneficial to preserve edges and smooth the noises. Furthermore, the tangential component is added to the external force field by later NBGVF snake model [17], which performs well on weak edge preserving and noise robustness. Yet the convergence capability of long and thin depression is still a nasty problem. Qin proposed the GGVF snake model based on component normalization (CN-GGVF) method on the basis of the studies about GGVF and GVF snake model. [18].

Moreover, the above methods have no ideal effect if images have complex edge structures and cluttered background. Incorrect convergence may happen, losing a lot of important foreground information.

To address the problems of driving the active contour to the object with complex boundary and cluttered background, not only can we put forward a novel external force that has a better performance in narrow and deep concavity convergence, noise robustness, and edge preserving, but also we present a multi-step decision model based on the new external force. The main contributions are summarized as follows:

(1) We propose a novel external force, called CN-AEGGVF, which integrates into the gradient information of image to preserve weak edges and add the normal and tangential self-adaptive weighting functions to the diffusion process so that it can adjust adaptively according to image characteristics. Furthermore, we also adopt the method of component-based normalization to enhance the ability of concavity convergence.

(2) We also present a new multi-step decision model based on CN-AEGGVF. Firstly, this model uses the CN-AEGGVF snake model for obtaining approximate contour of the interesting area's boundaries. Then, a new distance map is generated according to the approximate contour. Next, the new directional edge map is created by calculating a scalar product of the gradients of the distance map and initial image.

In the process, we adopt a narrow band method to reduce time complexity and make use of the gradient directional information and the magnitude information of the distance map to attenuate unwanted edges. Finally, a refined CN-AEGGVF vector field is built by this edge map to obtain more accurate contour.

This paper begins with an overview of classical snake model and GVF snake model in Section 2. In Section 3, the proposed method is exhibited and analyzed in details. Experimental results are displayed and the results are compared in Section 4. The conclusions are given in Section 5.

2. Related work

2.1. Conventional snake model

In the active contour model first proposed in [1], an energy minimizing curve (snake) is guided by external and internal energies to create a contour around an object. It can be expressed by $\mathrm{x}(s) = (x(s), y(s)), s \in [0, 1]$. The energy function is as follows:

$$\begin{aligned} E_{snake} &= \int_0^1 [E_{int}(\mathrm{x}(s)) + E_{ext}(\mathrm{x}(s))]ds \\ &= \int_0^1 \left[\alpha(s)\left|\mathrm{x}'(s)\right|^2 + \beta(s)\left|\mathrm{x}''(s)\right|^2 + E_{ext}(\mathrm{x}(s))\right]ds \end{aligned} \tag{1}$$

where $E_{int}(\mathrm{x}(s))$, the snake's internal energy or prior, is the weighted sum of first and second derivatives of $\mathrm{x}(s)$.

$E_{ext}(\mathrm{x}(s))$ represents external energy. $\alpha(s)$ is the elastic coefficient, and $\beta(s)$ denotes intensity coefficient.

Based on the variation principle [16], Eq. (1) satisfies Euler–Lagrange equation at the maximization of contour curve energy:

$$\alpha(s)\mathrm{x}''(s) - \beta(s)\mathrm{x}''''(s) - \nabla E_{ext}(\mathrm{x}(s)) = 0 \tag{2}$$