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Active contours driven by divergence of gradient vector flow

Qiang Li [a], Tingquan Deng [a,*], Wei Xie [b]

[a] Harbin Engineering University, Harbin 150001, PR China
[b] Harbin University of Science and Technology, Harbin 150001, PR China

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ABSTRACT

Gradient vector flow (GVF) is an important and widely used external force field for snake evolution. Due to difficulties in evolving over saddle points and stationary points of GVF field, snakes based on GVF suffer from a poor performance of dealing with complex geometries. In this paper, we investigate and analyze the characteristic of the divergence of GVF field and the flux of GVF field across the curve, to the end propose a geometric active contours model. In the new model, the external driving force just is the negative gradient of an energy functional. The proposed model greatly improves the active contours in dealing with complex geometries, and has good robustness and a wide capture range. In addition, from the differential geometry point of view, we give a uniform selection of the edge map used in computing GVF field for either a scalar or a vector-valued image. It makes the proposed model be implemented straightforwardly for both kinds of image. Various experiments are provided to demonstrate the capability of the proposed model in image segmentation and object recovery, especially when complex geometries are dealt with.

1. Introduction

Since the *snakes* model [1] was proposed, active contours have received numerous research [2–15], and been widely applied in image processing and computer vision for boundary extraction and image segmentation [16,17]. An active contour (or snake) is a curve that evolves within a digital image to locate object boundary. It is driven by two forces [18]: one is an internal force that is determined by the geometric property of the curve and ensures the curve regular. And the other is an external force that is derived from the image content and drives the curve evolution to the image feature of interest (e.g. boundary).

According to the essential origination of the external force, active contour models can be classified into two categories [19]: region-based models and edge-based models. In region-based models [20–23], the external force originates from the statistic characteristic of image. While in an edge-based model, the external force essentially originates from the local distinct difference or gradient of image. The edge-based models can also be fallen into either direct-gradient-based models or gradient-creating-external-force-field models. In direct-gradient-based models [1,24], the external force is derived from the gradient of a function of image gradient. Generally, since the image gradient is sensitive to noise, direct-gradient-based methods have poor robustness to noise, so effective pretreatment is required to smooth the image. Since distinct difference or large gradient often occurs at the vicinity of object boundary, direct-gradient-based methods generally have a poor capture range. In order to get better performance, the initial contour must be located

* Corresponding author.
E-mail addresses: liqiang99@hrbeu.edu.cn (Q. Li), deng.tq@hrbeu.edu.cn (T. Deng).

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near the object boundary [1]. In [24], the *geodesic active contours* (GAC) model was proposed, where a constant force was fitted in to extend the capture range and improve the convergence rate.

To solve the problems of the direct-gradient-based models associated with poor robustness to noise and contour initialization, and poor convergence to complex boundary, some gradient-creating-external-force-field models [25–31] were proposed. In such models, under certain principles, an external force field is created by using the image gradient (mainly by using the large image gradient), and the active contour evolution is implemented in the field. Gradient vector flow (GVF) [25] is such an external force field, important and widely used [32–35]. The main idea of GVF is diffusing the gradient vectors of the edge map, to the end creating a new vector field (GVF field) for snake evolution. By using the GVF field as the external force, Xu and Prince [25] proposed an active contours model, called *GVF snakes model*. GVF snakes model improves the active contours in having a wider capture area, converging to boundary concavities better, and being more robust to noise.

However, if there are several objects contained in an image, or an object to be recovered has a complex geometry, saddle points and stationary points may appear in the GVF field of the image. GVF snakes (snakes following GVF snakes model) trend to rest at the saddle points and always go away from the stationary points, so cannot evolve over such critical points and converge to the object boundary accurately. In other words, GVF snakes have poor capability of dealing with complex geometries. In order to overcome the drawback of GVF snakes, a general method is to introduce extra balloon forces into the GVF snakes model. However, the introduction of balloon forces may lead to a dilemma. If the consistency of the introduced balloon forces with the GVF external force is satisfactory, then the integrated approach cannot solve the problem to a large extent. For example, Paragios et al. [36] have proposed an adaptive balloon force, and fitted it into the GVF snakes model to determine the curve evolution when the GVF external force becomes inactive (especially when the vector of GVF field is nearly tangent to the active contour). But the proposed model cannot deal with stationary points [29], so has limited capability of dealing with complex geometries as well. On the contrary, if the consistency of the introduced balloon forces with the GVF external force is not good enough, then such two kinds of external forces may conflict locally. As finally makes the tradeoff of the external forces a challenge.

Kimmel et al. [37,38] considered the problem related to alignment measure of the curve normal and the image gradient, and proposed an external force for snake evolution, called *alignment term*. In theory, the alignment term can be used to give a variational explanation for Marr–Hildreth edge detector (that is defined by the zero crossing of the Laplacian): the Marr–Hildreth edge just maximizes the alignment measure of the curve normal and the image gradient. In applications, the alignment term can lead active contours to a more accurate edge location, especially when intensity inhomogeneity is presented in the image [37,38]. From a technical point of view, the alignment term is constructed by using the divergence of the image gradient field. Inspired by the work of Kimmel et al., in this paper, we investigate and analyze the characteristic of divergence of the GVF field. Based on the analysis, a new active contours model is proposed by using the negative gradient of an energy functional as the external force. The proposed model holds many features that the GVF snakes model has (e.g. good robustness to noise and a wider capture range), while it greatly improves the active contours in dealing with complex geometries. In comparison to the methods that introduce extra balloon forces, essentially, the proposed model just has one external force. Such a treatment makes one get rid of the dilemma of harmonizing and balancing the GVF external force and the balloon forces.

We note that, in [27], Li et al. proposed one method called *the segmentation of external force field* that suggests the active contour be split along stationary and saddle points to overcome the drawback of GVF snakes model related to dealing with complex geometries. While that strategy is inappropriate when the active contour is initialized inside the object boundary [29]. Compared to the segmentation of external force field, our model is geometric [18], designed in a different path and with more simple intuition. Our model can be used to recover objects with more complex geometry (especially with interior boundaries) and be implemented more conveniently. To our knowledge, as a gradient-creating-external-force-field model MAC [29] has a satisfying performance of dealing with complex geometries. However, its computation is complex and expensive (refer to [29]). In addition, it is worth pointing out that, region-based methods generally have excellent capability of dealing with complex geometries, for example, [5,11,15].

Edge map taking a larger value on the object edge is an important base of the GVF method. Generally, a proper selection of edge map leads to an efficient GVF field and then a better result of image segmentation. The original GVF method [25] is proposed for the gray-scale image segmentation. In this paper, we also consider the selection of edge map and the extension of GVF method to the vector-valued image segmentation. There are many works on the edge map of vector-valued image. Zenzo [39] and Sapiro [40] presented detailed discussions on the gradient of vector-valued image for image segmentation. By regarding an image as a submanifold embedded in a higher dimensional Non-Euclidean space, Sochen et al. [41] gave a representation of color image and proposed a related edge map to carry out image segmentation. Sagiv et al. [42] interpreted an image as a Riemannian submanifold embedded in a higher dimensional Euclidean space and introduced an integrated active contours model for texture segmentation. In addition, Wang et al. [5] comprehensively depicted features of pixels (e.g., gray value and the local geometrical features, such as orientation and gradient) as a three-order tensor, and then extended the famous Chan–Vese [20] model to texture segmentation. In this paper, from the differential geometry point of view we consider an image as a Riemannian manifold (surface) embedded in a higher dimensional Euclidean space and present a uniform framework of