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Level set evolution driven by optimized area energy term for image segmentation

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ABSTRACT

As a classic and famous active contour model for image segmentation, distance regularized level set evolution method avoids the process of re-initialization and can segment images flexibly, but it is easy to leak from objects with weak boundaries and fall into false boundaries. In this paper, an improved level set evolution model is proposed, in which an optimized area energy term combining a region growing matrix and an adaptive boundary indicator function is added to effectively detect boundaries for images with several adjacent targets and accelerate convergence at the same time. With an adaptive boundary indicator function involving a threshold defined by the standard deviation of images to be detected, this model can cross false boundaries and implement a correct segmentation for low contrast images. Meanwhile, the double-well potential function is optimized to make the model more stable. Experimental results on images of different objects have proved that the proposed model not only improves the precision of locating boundaries but also reduces the computational cost and works a stronger robustness than some other edge-based active contour models.

1. Introduction

Image segmentation divides an image into some disjoint parts to extract the objects of interest, which has a direct impact on the subsequent image processing and analysis, including describing targets, measuring characteristics and reconstructing 3D models, etc. It has been studied for about 40 years, during this period, a variety of segmentation methods based on different theories emerged, for example, K-means algorithm [1] based on clustering theory, C- means algorithm [2] based on fuzzy theory, and active contour models (ACMs) [3–7] based on partial differential equations. K-means algorithm uses distance as indicator to evaluate similarity. The objects in one image are divided into some clusters and each cluster has high similarity. Finally, the compact and independent cluster is the segmentation result. The general idea of C-means algorithm is similar to K-means algorithm, the difference is that C-means algorithm uses the probability density function to judge the possibility that it belongs to every cluster.

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In recent years, various forms of ACMs, such as snake models [8] and level set methods (LSMs) [5,9–14], have been popularly applied in the image segmentation. According to different representations for evolution curves and different implementation forms, ACMs can be divided into two classes: parametric ACMs [15] and geometric ACMs [10,16]. Parametric ACMs use a parametric curve to explicitly represent the evolution curve while geometric ACMs use the zero level set of the signed distance function defined in a higher dimensional space to implicitly represent the evolution curve. Compared with parametric ACMs, the widely-used LSMs, one of geometric ACMs, have many advantages [16]. The most important one is that LSMs are able to utilize the implicit representation of the evolution curve to track contours with complex topology and handle their topological deformation, such as splitting, merging and so on, in a natural way.

The earliest LSM [9] was proposed by Osher and Sethian. Due to the fact that these methods must ensure the level set function be kept as a sign distance function during its evolution, the process of re-initialization [17] is typically used in LSMs. Although many methods [5,17,18] were presented to realize the re-initialization of the level set, almost all of them realize it by solving a partial differential equation irregularly during the iteration of the level set function, which leads to a large computational cost. The basic level set algorithms can be divided into two categories: region-based LSMs [14,19] which make use of similarity within the region; edge-based LSMs [10,13,20] which mainly utilize different gradient information in an image. Chan and Vese, by introducing the Mumford-Shah model [21] into the level set method, bulit one of the most famous model in region-based LSMs, namely Chan-Vese (CV) model [6], to achieve linear segmentation results toward piecewise images. This method, instead of defining boundaries with the image gradient, considers the segmentation problem as an optimization problem. It can obtain the optimal piecewise linear representation of the image by minimizing the energy functional. It is essentially a piecewise linear representation of the image, which means it can only segment images with homogeneous objects and background, so it is not ideal for the segmentation of non-homogeneous images. Literature [22] gives the method of automatically adjusting the parameters in the region-based LSMs with local image geometry. Liu et al. [23] proposed a local Chan–Vese model based on region. Although it has high efficiency, it is easy to be affected by the initial contour. At present, the local image fitting (LIF) energy model [24] proposed by Zhang, the local binary fitting (LBF) model [25] and the distance regularized level set evolution (DRLSE) model [20] proposed by Li et al, which are classified into edge-based LSMs, can relatively implement successful segmentation for non-homogeneous images.

The DRLSE model, a variational level set method presented by Li et al, involves a penalty term into the energy functional to reduce the deviation between the level set function and the signed distance function in each iteration, which completely eliminates the need of re-initialization. However, this representative method uses a stopping force based only on image gradient, which will lead the zero level set to evolve with an inappropriate speed in some regions. As a result, when images have weak boundaries or even have more than one target, its final segmentations often have obvious deviation from the correct position. Although many improved methods [13,14,26–30] on the basis of DRLSE were proposed every year, the factors, including blurry edges caused by gauss smoothing, the convex boundary in images and some others, bring difficulties to the use of DRLSE. For example, based on the DRLSE model, He et al. [31] replaced the coefficient of area term with the sign of the image gradient change, which reduced the sensitivity to initial contours. Although the robustness and accuracy of this method for different images need to be further improved [32], this method provides a kind of new thought to solve these problems. Subsequently, Wang and He proposed an adaptive level set evolution [33], which modified the area coefficient into a variable sign function to improve the robustness to initial contours. It greatly improved the segmentation speed and has a good performance on segmentation in the case of clear edges or background with low noise. However, this model has poor anti-noise ability and is easy to leak from weak edges. Literature [27] introduces a nonlinear adaptive level set method (NLALS) driven by a nonlinear adaptive velocity and a novel stop force to adjust evolution for image segmentation, but it can't work well for weak edges of multi-objects and evolves slowly. For the noisy and texture images, active contour model driven by the energy from the local Gaussian distribution fitting is presented in literature [34], but it usually spends much computational cost.

In this paper, in order to solve some of the problems aforementioned, we propose an improved level set evolution model based on an optimized double-well potential function and an enhanced area energy term combining a region growing matrix and an adaptive boundary indicator function. First, the evolution rate of the double well-potential function is improved according to the expected force and speed to be regulated in different ranges, which makes this model not only avoid the occurrence of re-initialization but also become more stable when adding this function into the distance regularized term. Then, the adaptive boundary indicator function in this model can deal with boundary leakage and improve the anti-noise capability by adaptively choosing the value of a boundary threshold containing the global image information. In addition, due to the blurred edges influenced by Gaussian filter, we add a regional growth function to enhance the energy between adjacent targets, which can realize an accurate segmentation for multiple objects and speed up convergence. Compared with other major edge-based LSMs, our model can work a stronger robustness and achieve a better segmentation for images in terms of accuracy and efficiency.

The rest of this paper is organized as follows: Section 2 briefs the DRLSE model and the NLALS model, and makes an analysis on the drawbacks of the DRLSE model. The next section describes the proposed model in detail. Section 4 gives the experimental results and presents a further comparison and discussion. Section 5 makes some discussions on the proposed model. Finally, the work is summarized in Section 6.