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An active contour model and its algorithms with local and global Gaussian distribution fitting energies

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ABSTRACT

In this paper, we propose an active contour model and its corresponding algorithms with detailed implementation for image segmentation. In the proposed model, the local and global region fitting energies are described by the combination of the local and global Gaussian distributions with different means and variances, respectively. In this combination, we increase a weighting coefficient by which we can adjust the ratio between the local and global region fitting energies. Then we present an algorithm for implementing the proposed model directly. Considering that, in practice, the selection of the weighting coefficient is troublesome, we present a modified algorithm in order to overcome this problem and increase the flexibility. By adaptively updating the weighting coefficient and the time step with the contour evolution, this algorithm is less sensitive to the initialization of the contour and can speed up the convergence rate. Besides, it is robust to the noise and can be used to extract the desired objects. Experiment results demonstrate that the proposed model and its algorithms are effective with application to both the synthetic and real-world images.

1. Introduction

Image segmentation is always one of the major problems in image analysis and computer vision. In the past twenty years, numerous different approaches have been continuously proposed for handling this problem, such as those recent methods based on the fuzzy Dempster-Shafer inference system [16] and the feature space [36]. Due to the good performance, active contour models [8,9,12,19] based on the theory of curve and surface evolutions and geometric flows have been extensively studied and successfully used in the field of image segmentation. With explicit parametric curves, the original active contour model was introduced in [19] for extracting objects. As indicated there, this model has some intrinsic disadvantages, such as its difficulty in handling topological changes. In order to overcome this difficulty, level set method [29] which was firstly proposed by Osher and Sethian could effectively handle topological changes by representing curves or surfaces as the zero level set of a high dimensional function. Since the introduction of the level set method, it has become increasingly popular in many aspects of image processing and analysis. Furthermore, it is specially applied to develop active contour models for image segmentation.

Generally speaking, active contour models can be categorized into two different classes: edge-based models [9,15,30,39,43] and region-based models [12,20,22,23,34,35,38]. Edge-based models use the edge information to drive the active contour toward the object boundaries and stop there. This kind of models is sensitive to initial conditions and some-

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times with some boundary leakage problems, especially to the weak or fuzzy boundaries. Compared with the edge-based models, region-based models do not rely on any edge and gradient information and are less sensitive to the noise and clutter. Moreover, the region-based models are usually less dependent on the initialization since they exploit the global region information of the image statistics. Therefore, in this paper, we mainly focus on the region-based models.

A large variety of region-based models and their related algorithms have been presented over the last twenty years and among them an increasingly prevalent kind of approaches is mainly concerned with the application of statistical methods [13]. These approaches are to define the data term usually by introducing statistical parametric models where each segmentation region is characterized by a set of parameters. In this way, it can distinguish the region from the others, such as the models based on Gaussian distribution [27,48], Gamma distribution [2], Weibull distribution [1], Wishart distribution [4], Rayleigh distribution [35] and Fisher-Tippett distribution [18]. These models are mainly stated by maximizing a likelihood estimation or maximizing a posteriori probability, which can be conditionally transformed to minimizing an equivalent energy functional. One of the most popular region-based models is Chan-Vese (C-V) model [12], which, as a special case of Mumford-Shah energy functional [28], is defined by minimizing an energy functional to approximate the image in piecewise constant forms. On the basis of the C-V model, in [6,7,10], the authors further present and develop a series of global minimization methods. However, the C-V model is always based on the assumption that the image is statistically intensity homogeneous in each region so that it exists some limitations in practical applications. In fact, intensity inhomogeneous images widely exist in the real world, such as medical imaging due to some technical limitations or artificial factors. As a whole, intensity inhomogeneity is still considered as a challenging problem in image segmentation. Based on the single level set model, a multiphase level set framework [40] is presented for the multi-region image segmentation, which can be used to deal with the problem of intensity inhomogeneity. However, it requires periodical reinitialization of the level set function so that the computational cost is expensive. And especially for the image with severe intensity inhomogeneity, the effectiveness is unsatisfactory. Later on, local region information has been incorporated into the active contour models and it is worth mentioning that local binary fitting (LBF) model [22,23], also called region-scalable fitting model, performs better than the C-V model on extracting objects for the image with intensity inhomogeneity. But the LBF model is sensitive to the initialization of the contour. And especially if the initial position of the contour is far away from the object boundaries, the LBF model may be prone to getting stuck in local minima.

In practice, how to effectively integrate the advantages of the local and global region information plays an important role in improving the segmentation quality. Apart from the LBF model, in [21,41,45], active contour models mainly based on the local region information are further developed in various ways, which are effective to the image with intensity inhomogeneity. In [5,42], on the basis of complementary advantages, the local and global region information are incorporated with each other to increase the flexibility and obtain more desirable results. On the other hand, based on the consideration of image information and application, a major concern is to obtain the selective objects [3,32,46], which has some positive significance particularly with application to medical imaging in order to extract the partial desired objects for helping medical diagnosis.

Among the region-based models, in the following we pay attention to the introduction of statistic methods. For simplicity, let $I : \mathbf{x} \in \Omega \rightarrow R$ be a given image, where $\mathbf{x}$ is a vector to represent a point in the domain Ω. Similarly to [13,31,35], we assume that the intensity of each point is a random variable and its pixel intensity in each local region is independent and identically distributed. Without loss of generality, we consider a two-region image segmentation problem based on the statistical methods. Generally the problem of maximizing likelihood estimation or maximizing a posterior probability based on probability density functions is equivalent to minimizing an energy functional with their negative logarithm forms expressed as follows:

$$E(I(\mathbf{x}), C) = -\int_{\Omega_1} \log p(I(\mathbf{x}); \Omega_1) d\mathbf{x} - \int_{\Omega_2} \log p(I(\mathbf{x}); \Omega_2) d\mathbf{x}, \tag{1}$$

where Ω_1 and Ω_2 represent inside and outside regions of the contour C, respectively.

In this paper, based on the merits of the local and global region fitting energies, such as the LBF model and the C-V model, respectively, we firstly propose an active contour model. In this proposed model, the local and global region fitting energies are described by a combination of the local and global Gaussian distributions with different means and variances, respectively. In this combination of the proposed model, we increase a weighting coefficient by which we can dynamically adjust the ratio between the local and global region fitting energies. Subsequently, we introduce the level set method to realize the contour evolution and deduce the corresponding gradient descent flow equation, which can be easily implemented by the finite difference method. Secondly, we present an algorithm for implementing the proposed model directly. Nevertheless, in practice, the selection of the weighting coefficient is not an easy task. If we set a large weight coefficient, we cannot effectively deal with the image with intensity inhomogeneity. On the contrary, if we set it to be small, the proposed model is with slow convergence and sensitive to the initialization of the contour. In summary, the selection of a suitable weighting coefficient needs a large number of trials and modifications and the process is time-consuming. To overcome this problem, we further present a modified algorithm in which the weighting coefficient and the time step of the iteration can be adaptively updated with the contour evolution. That is to say, we can obtain an adaptive weighting coefficient and a fit time step, which are helpful to detect the object boundaries and speed up the convergence rate. More specifically, for the convenience of the initialization of the contour, sometimes we can set a relatively large weight coefficient at the beginning. And then when the