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A narrow band interval type-2 fuzzy approach for image segmentation

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ABSTRACT

Traditional fuzzy sets capture vagueness through precise numeric membership degrees. This poses a dilemma of excessive precision in describing uncertain phenomenon. Interval type-2 fuzzy sets have shown its effectiveness in handling uncertainties in comparison to the traditional fuzzy sets. In this paper, the interval type-2 fuzzy approach is introduced into the framework of active contour model, which effectively segment images with large uncertainties. However, the computational cost is largely increased by employing the interval type-2 fuzzy set. Therefore, we try to update the pixels within a narrow band region near the contour boundary for reducing the computational cost caused by employing the interval type-2 fuzzy set. Moreover, both spatial and gray constraints are taken into consideration when calculating the fuzzy membership value to retain more image details. Experimental results on synthetic and real images show that the proposed method is effective and efficient, and is relatively independent of initial conditions.

1. Introduction

Image segmentation is one of the fundamental tasks in image understanding and computer vision. The task of image segmentation is to divide an image into non-overlapping regions, which have same characteristics such as gray level, tone, texture, etc. Image segmentation has been successfully applied to a variety of real applications, such as medical imaging, object recognition, synthetic aperture radar image understanding, etc. [1–5]. In literatures, various techniques have been proposed for image segmentation [6,7], such as histogram thresholding, region-growing, clustering, active contour models, graph-cut methods and so forth. However, due to the complexity of several images, designing a more robust and efficient segmentation method is still the common pursuit of researchers.

Active contour models (ACMs) [8] have been extensively applied to image segmentation. There are several desirable advantages of ACMs over classical image segmentation methods. ACMs can be easily formulated under a principled energy minimization framework, and allow incorporation of various prior knowledge, such as shape and intensity distribution, for robust image segmentation. They can also provide smooth and closed contours as segmentation results, which are necessary and can be readily used for further applications, such as shape analysis and recognition. Due to its capabilities, ACMs are successfully applied to many fields, such as feature extraction, image registration, object detection, motion tracking and industrial [9–14]. The core part of ACMs for image segmentation is that a curve which is evolved subject to the characteristics of the image is employed, and then objects can be extracted by optimizing an energy function.

Most of the ACMs studied under the level set framework can be categorized into two types: edge-based and region-based ones. The performance of edge-based models which use energy functions on the basis of edge information is inadequate, since only the objects with edges defined by gradient can be detected. For comparison, many enhanced models have been proposed on designing complex region-based energy functions, which are less sensitive to noise and can detect objects with weak boundaries. Region-based models utilize not only image information near the evolving contour, but also statistics information inside and outside the evolving contour. Although they enjoy excellent performance, defects within these models are still not fully eliminated. A detrimental condition for many ACMs is that they are defined as the partition of an image into non-overlapped and consistent regions which are homogeneous with respect to some image characteristics such as gray value or texture. However, in real applications, it may be impossible to obtain such images. Due to technical limitations or artifacts introduced by the object being imaged, intensity inhomogeneities often occur in real-world images from different modalities and may cause considerable difficulties in image segmentation. For example, intensity inhomogeneity in magnetic resonance (MR) images arises from the nonuniform magnetic fields produced by radio-frequency coils as well as from variations in object susceptibility. It often appears as the variation of intensities from the same tissue type over the locations in an image. Without an effective preprocessing step such as intensity inhomogeneity correction or histogram equalization, segmentation is

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difficult to implement. Issues such as limited spatial resolution, noise and intensity inhomogeneities may reduce the effectiveness of traditional ACMs.

Soft computing techniques provide a flexible way for processing information. Fuzzy logic, a widespread soft computing technique, has been applied to many clustering and image segmentation methods [15–21]. Fuzzy energy-based active contour model (FAC) was proposed by Krinidis and Chatzis [22], which first combines fuzzy logic with the active contour methodology. It can handle objects whose boundaries are not necessarily defined by gradient, objects with very smooth or even with discontinuous boundaries. The FAC model has good ability to reject local minima, which is benefit from the characteristic of fuzzy logic. It is also able to detect objects with discontinuous or smooth edges.

The traditional fuzzy set tends to capture vagueness through precise numeric membership degrees. This poses a contradiction of excessive precision in describing uncertain phenomenon. The membership degree is more reasonable to be taken as uncertain instead of as certain in the traditional fuzzy set. Thus, fuzzy active contour models that built on the basis of the traditional fuzzy set have the limitation of handling various uncertainties in images. Interval type-2 fuzzy sets, as an extension of the traditional fuzzy set, applies a secondary membership to define the possibilities of the primary membership [23]. The interval type-2 fuzzy set has shown its effectiveness in handling uncertainties in comparison to the traditional fuzzy set. However, incorporating the type-2 fuzzy logic drastically increases computational cost due to the type reduction process in interval type-2 fuzzy set. The issue on reducing computational cost needs urgent attention when employing the interval type-2 fuzzy set-based algorithms.

The management of uncertainty using the intervaltype-2 fuzzy set has been applied to various fields where we cannot obtain satisfactory performance by the traditional fuzzy set, such as control of mobile robots, inference engine design, transport scheduling, pattern recognition, etc. [24–27]. In this paper, we will propose an enhanced ACM by employing the interval type-2 fuzzy set. In particular, our work is highlighted as follows: (1) With the extension of traditional fuzzy sets into interval type-2 fuzzy sets, uncertain knowledge or information of an image will be well described by uncertain membership values; (2) The pixels within a small selected region are updated at each iteration, which enables the contour to evolve gradually and reduces the computational cost on the employment of the interval type-2 fuzzy set. (3) The spatial constraint providing more image details has been intensively used in image segmentation algorithms. In the proposed model, the weighted fuzzy factor which takes both spatial and gray constraints into consideration is designed for computing the type-2 fuzzy membership value. Experimental results demonstrate the good performance of the designed enhanced ACM for image segmentation.

The rest of this paper is organized as follows. In Section 2, the main ideas of the proposed techniques and our motivation are introduced. Section 3 describes the proposed method in detail. In Section 4, experimental results on synthetic and natural images are described. Conclusions are drawn in Section 5.

2. Motivation

In ACMs, the segmentation process is the evolution of a curve subject to image characteristics such that the desired objects can be extracted by minimizing an energy function. Assume that the image I is formed by two regions. The curve C which defines the boundaries of the segmentation region is iteratively evolved according to the characteristics in the image domain Ω. The object to be detected is represented by the region inside the curve C, while the background is represented by the region outside the curve C.

One of the most widely used ACM is the CV model. In CV model, an initial partition of the image is provided firstly. This initial partition will be iteratively evolved according to the image characteristics in the image domain Ω by a minimization process. The curve C defines the boundary of the desired objects. For a given image I, they proposed to minimize the following energy function [9]:

$$E^{CV}(c_1, c_2, C) = \mu \cdot \text{Length}(C) + \lambda_1 \sum_{\Omega} (I(x, y) - c_1)^2 + \lambda_2 \sum_{\Omega} (I(x, y) - c_2)^2 \tag{1}$$

where c_1 and c_2 are the average intensities of regions inside and outside of the evolving curve C, respectively, (x, y) is the spatial coordinate of a pixel, $I(x, y)$ is the gray value of the pixel located at (x, y), $\lambda_1, \lambda_2 > 0$ and $\mu \geq 0$ are fixed parameters. The energy function includes internal and external terms. The internal energy controls the smoothness of the contour, whereas the external energy attracts the contour toward the boundaries of objects. The first term in Eq. (1) is a regularization term for smoothing evolving curve C.

Traditional ACMs are designed on the assumption that images are approximated by non-overlapped and consistent regions which are homogeneous with respect to some image characteristics such as gray value or texture. Under the influence of spatial resolution or noise, pixels intensities belonging to object region and the background are generally overlapping, which may reduce the effectiveness of traditional ACMs on image segmentation.

2.1. Motivation of introducing the interval type-2 fuzzy set

Performance of image segmentation methods can be improved depending on how various uncertainties are properly handled. Fuzzy logic could process information in a flexible manner that well retains more information from the primordial image and has robust characteristics of ambiguity [18,22]. Compared with ACMs using hard energy functions, with the introduction of fuzzy logic into the framework of ACM, ACMs using fuzzy energy functions have the potential to avoid being trapped into local minima and provide a better judgment of overlapping clusters. Attributed by their fuzzy nature, fuzzy energy-based active contour model (FAC) was proposed by Krinidis and Chatzis [18], which first combines fuzzy logic with the active contour methodology. In the FAC model, the segmentation process is defined as the minimization of a fuzzy energy function [18,22]:

$$F(C, c_1, c_2, u) = \mu \cdot \text{Length}(C) + \lambda_1 \sum_{\Omega} [u(x, y)]^m (I(x, y) - c_1)^2 + \lambda_2 \sum_{\Omega} [1 - u(x, y)]^m (I(x, y) - c_2)^2 \tag{2}$$

where c_1 and c_2 are the average intensities of regions inside and outside of the evolving curve C, respectively, (x, y) is the spatial coordinate of the pixel, $u(x, y)$ is the membership degree of pixel (x, y) belonging to the inside of C, where m is the fuzzy coefficient, $I(x, y)$ is the gray value of the pixel located at (x, y), $\lambda_1, \lambda_2 > 0$ and $\mu \geq 0$ are fixed parameters. The first term in Eq. (2) is the length term, which accounts for smoothing the curve. μ is used to control the effect of the length term. According to [18,22], the length term is not important for a clean image. For simplicity, without loss of generality, the length term has not been considered when minimizing the fuzzy energy function. λ_1 and λ_2 are used to control the weights of distances between pixels and average prototypes of the image regions inside and outside C, respectively. λ_1 and λ_2 are generally set to 1 for balancing the weights of two regions in Eq. (2).

In fuzzy energy-based active contour model models pixels are assigned to various image regions with different degrees of belonging. The membership degree which reflects the degree of a pixel belonging to the object region is computed as follows: