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Object(s)-of-interest segmentation for images with inhomogeneous intensities based on curve evolution

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ABSTRACT

In this paper, we propose an object(s)-of-interest (OOI) segmentation method for images with inhomogeneous intensities. First, we define a discrimination function for each pixel, labelling whether the pixel belongs to OOI based on the characteristics of OOI. This function is then integrated with image gradient to construct a stopping function in an energy functional. Finally, this energy functional is minimized by means of level set evolution, which guides the motion of the zero level set toward object boundaries. The results demonstrate that our model is effective.

1. Introduction

Image segmentation is one of the core tasks in image processing, computer vision and pattern recognition. Its goal is to partition an image into constituent and disjoint subregions, which are uniform according to their features such as intensity, color and texture. As a special case, object(s)-of-interest (OOI) image segmentation has been becoming more and more important in various fields. Therefore, how to design an efficient and robust method for image segmentation, especially for OOI, is an issue not only in computer science but also in applied mathematics.

A variety of segmentation methods based on curve evolution theory and level set methods have been proposed. Their basic idea is to represent a contour as the zero level set of a higher dimensional level set function, and formulate the contour motion as the level set evolution.

The existing curve evolution models can be categorized into two classes: edge-based and region-based models. These two types have their own merits, and which one to choose in applications depends on image characteristics. Edge-based models utilize image gradients to guide the level set evolution. For example, the popular Geodesic Active Contours (GAC) model [1] constructs an edge stopping function to attract the active contour to object boundaries. The edge-based methods, unfortunately, have drawbacks such as sensitive to noise and weak edges. To prevent these limitations, region-based methods utilize the region information, such as intensity, to guide the contour evolution. One of the well-known region-based active contour models is the Chan–Vese model [2].

All these methods, however, focus on segmenting all objects in images. In some occasions our aim is to segment only OOI. For instance, the OOI segmentation has wide applications in content-based image retrieval, object recognition, hippocampus segmentation in clinical studies, etc. Then, these methods cannot segment the desired object(s) alone.

In order to extract the OOI, a variety of algorithms based on the learning techniques, where a classification model is trained to determine whether a region or a pixel belongs to the OOI, were proposed. Ko and Nam [3,4] used a support vector machine (SVM) [15] to cluster the salient regions into OOI. Gondra et al. [5] used multiple instance learning to determine which regions in an over-segmented image are part of the OOI. Angelova and Zhu [6] trained a linear SVM classifier on super-pixel regions and used a Laplacian-based propagation to segment the full object. Their algorithms are only suitable in the case that databases were given.

Pi and her coauthors [7–11] proposed some semi-automatic methods for OOI delineation using the modified GAC and the modified Chan–Vese models. They first visually chose sample pixels from the OOI. Then, they obtained the discrimination function for OOI by principal component analysis and interval estimation. The discrimination function can help to locate an

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initial contour. Finally, the segmentation of OOI are obtained from modified curve evolution models.

These models, however, fail to segment OOI with intensity inhomogeneity. In fact, intensity inhomogeneity occurs in many real images of different modalities. To deal with this problem, local region-based methods have been developed to handle intensity inhomogeneity caused by spatial variations in illumination. Typically, Li et al. [12–14] proposed a Local Binary Fitting (LBF) energy. The LBF model utilizes the local intensity means inside and outside the contours to guide the level set function evolution.

Inspired by previous works, in this paper we propose a novel OOI segmentation method to segment images with inhomogeneous intensities. We first introduce a discrimination function to label each pixel based on the characteristics of OOI's. This function is then integrated with image gradient to define a stopping function and form an energy functional. Then, this energy functional is minimized by means of level set evolution, which guides the motion of the zero level set toward the object boundaries.

The remainder of this paper is organized as follows. In Section 2, we discuss some edge based and region based models and their limitations. Section 3 describes our model and its level set formulation. Section 4 reports the experimental results. Conclusions are drawn in Section 5.

2. Related works

In this section, we review some classical active contour models: the GAC model, the Chan–Vese model, the modified Chan–Vese (MCV) model and the LBF model.

2.1. The GAC model

Given a gray image I and a closed initial curve $\mathcal{C}$ on I, the GAC model is to minimize the following energy functional:

$$L_R(\mathcal{C}) = \int_0^{L(\mathcal{C})} g(|\nabla I[\mathcal{C}(s)]|)\, ds, \tag{1}$$

to obtain the object contour, where $L(\mathcal{C})$ denotes the curve length, $L_R(\mathcal{C})$ is the weighted length, and g is any monotonically decreasing non-negative function called the edge stopping function. Without loss of generality, g can be chosen as

$$g(|\nabla I|) = \frac{1}{1+\frac{|\nabla I|^2}{K^2}}, \tag{2}$$

where $K > 0$ is a parameter.

The main drawback of the GAC model is the non-convexity of the energy, which can lead to local minimal problem and sensitive to noise and weak edges.

2.2. The Chan–Vese model

To overcome the drawback of the GAC model, Chan and Vese proposed an active contour model based on region information. For an image I on the image domain Ω, the Chan–Vese model is to minimize

$$E^{CV}(\mathcal{C}, c_1, c_2) = \lambda_1 \int_{\mathcal{C}_{in}} |I(\mathbf{x}) - c_1|^2\, d\mathbf{x} + \lambda_2 \int_{\mathcal{C}_{out}} |I(\mathbf{x}) - c_2|^2\, d\mathbf{x} + \nu |\mathcal{C}|, \tag{3}$$

where λ_1, λ_2 and ν are positive constants, $\mathcal{C}_{in}$ and $\mathcal{C}_{out}$ represent the regions inside and outside the contour $\mathcal{C}$ respectively, $|\mathcal{C}|$ is the contour length, and c_1 and c_2 are two constants which fit the average image intensity inside and outside the contour $\mathcal{C}$.

The Chan–Vese model focuses on segmenting all objects in the image. When only OOI is concerned, the Chan–Vese model fails.

2.3. The modified Chan–Vese model

The modified Chan–Vese (MCV) method [10] is for OOI delineation. The difference between the Chan–Vese model and the MCV model is that the new stopping function in the MCV model, which can guide the evolved curve to OOI boundaries, is adopted. The MCV model first visually chose sample pixels from the OOI, then used these sample pixels to construct a discrimination function for OOI by the principal component analysis and interval estimation. A stopping function incorporated the discrimination function to contain the information of OOI. This stopping function replaced the original stopping function in the Chan–Vese model.

However, if the image intensity in either $\mathcal{C}_{in}$ or $\mathcal{C}_{out}$ is not homogeneous, such global fitting might not be accurate. Thus, the MCV model may fail to handle intensity inhomogeneity.

2.4. The LBF model

To segment images with inhomogeneous intensity, Li et al. proposed a local region based model using image intensity information in local regions. For an image I on the image domain Ω, and a given point $\mathbf{x} \in \Omega$, let $\mathcal{C}$ be a contour in I. A local fitting energy is defined as

$$\begin{aligned} E_{\mathbf{x}}^{LBF}(\mathcal{C}, c_1(\mathbf{x}), c_2(\mathbf{x})) = {} & \lambda_1 \int_{\mathcal{C}_{in}} K_\sigma(\mathbf{x}-\mathbf{y})|I(\mathbf{y}) - c_1(\mathbf{x})|^2\, d\mathbf{y} \\ & + \lambda_2 \int_{\mathcal{C}_{out}} K_\sigma(\mathbf{x}-\mathbf{y})|I(\mathbf{y}) - c_2(\mathbf{x})|^2\, d\mathbf{y}, \end{aligned} \tag{4}$$

where λ_1 and λ_2 are positive constants, $c_1(\mathbf{x})$ and $c_2(\mathbf{x})$ are two constants that fit image intensities around $\mathbf{x}$ inside and outside the contour $\mathcal{C}$, and $K_\sigma(\mathbf{x}-\mathbf{y})$ is the Gaussian kernel function

$$K_\sigma(\mathbf{x}-\mathbf{y}) = \frac{1}{(2\pi)^{\frac{n}{2}}\sigma^n} e^{-\frac{\|\mathbf{x}-\mathbf{y}\|^2}{2\sigma^2}}. \tag{5}$$

Note that $K_\sigma(\mathbf{x}-\mathbf{y})$ has the localization property that it takes larger values at the points $\mathbf{y}$ near the center point $\mathbf{x}$, and it decreases to zero as $\mathbf{y}$ goes away from $\mathbf{x}$. Consider all center points $\mathbf{x}$ in the image domain Ω, the total LBF energy functional is defined as follows:

$$E^{LBF}(\mathcal{C}, c_1, c_2) = \int_\Omega E_{\mathbf{x}}^{LBF}(\mathcal{C}, c_1(\mathbf{x}), c_2(\mathbf{x}))\, d\mathbf{x}. \tag{6}$$

By minimizing the energy functional, the object boundary is obtained.

3. Our model and algorithm

These active contour methods, however, cannot be directly applied to OOI image segmentation. The key reason is that the evolving contour may stop at some non-OOI points. Usual stopping function is a decreasing function of the gradient and it only depends on the gradient. Therefore, the evolution curve of the level set method may stop at a location with large gradient, but that location may not indicate our OOI correctly. In this paper, we define a proper stopping function: it is small if and only if the following two conditions hold: (1) the point belongs to the OOI, and (2) that point has a large gradient. We will construct such a stopping function in Section 3.2

In this section, we first introduce a discrimination function to label each pixel based on the characteristics of OOI. Then the discrimination function is integrated with image gradient to define