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Level set evolution with locally linear classification for image segmentation

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ABSTRACT

This paper presents a novel local region-based level set model for image segmentation. In each local region, we define a locally weighted least squares energy to fit a linear classifier. With level set representation, these local energy functions are then integrated over the whole image domain to develop a global segmentation model. The objective function in this model is thereafter minimized via level set evolution. In this process, the parameters related to the locally linear classifier are iteratively estimated. By introducing the locally linear functions to separate background and foreground in local regions, our model not only achieves accurate segmentation results, but also is robust to initialization. Extensive experiments are reported to demonstrate that our method holds higher segmentation accuracy and more initialization robustness, compared with the classical region-based and local region-based methods.

1. Introduction

In the past few years, a number of works on geometric active contours, which are implemented via level set methods, have been proposed to address several problems in computer vision, such as image segmentation [1,2], visual tracking [3–5] and image de-noising [6–8]. Geometric active contours, which were introduced by Malladi et al. [9,10], are built on curve evolution theory and level set methods. The basic idea is to represent a contour as the zero level set of a higher dimensional level set function, and formulate the motion of the contour as the evolution of the level set function.

Existing active contour models can be broadly categorized into two classes: the edge-based methods [2,3,11–16] and the region-based methods [6,17–26]. Edge-based methods utilize image gradients to guide the level set evolution. For example, the popular Geodesic Active Contours (GAC) model [14,27,28] constructs an edge stopping function to attract the active contour to the object boundaries. Unfortunately, the edge-based methods have several drawbacks, such as sensitive to image noise and weak edges. To prevent these limitations, region-based methods utilize the region information, such as intensity, to guide contour evolution. One of the widely used region-based active contour model [17,6,18] utilizes Mumford–Shah techniques to achieve binary phase segmentation. It assumes that the image regions are statistically homogeneous. Recently, Zhang et al. [23] proposed a new region-based signed pressure force function to stop the zero level set at weak edges. Compared with the edge-based methods, the region-based models have two advantages. First, region-based models are more robust to image noise and have higher segmentation accuracy for images with weak edges. Second, they are less sensitive to the placement of initial curve. However, region-based models using global statistics may fail to segment the images with intensity inhomogeneity. In practice, intensity inhomogeneity occurs in many real-world images.

Recently, local region-based methods [29–33] have been developed to handle intensity inhomogeneity. Typically, Li et al. [29,30] proposed a Local Binary Fitting (LBF) energy to deal with intensity inhomogeneity. The LBF model utilizes the local intensity means inside and outside of the contours to guide the evolution of the level set function. To explicitly model images with intensity inhomogeneities, Li et al. [33] integrated LBF with multiplicative model of intensity inhomogeneity. Segmentation and bias field estimation are therefore jointly performed by minimizing the proposed energy functional. Motivated by the LBF model [30], Gaussian distribution was applied to describe the local image intensities [32], where the local Gaussian distribution fitting (LGF) energy is presented to guide the evolution of the level set function. By extracting local image information, these methods are able to segment images with intensity inhomogeneities. Although these local region-based methods have better performance than region-based methods and edge-based methods in segmentation accuracy, they are sensitive to the initial contour and easy to produce segmentation errors [34], which limits their practical applications.

Actually, a key task in local region-based models is to choose an appropriate model to separate the background and foreground in local region. Motivated by previous works [23,30,32], we

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propose a new locally linear classification (LLC) based model. First, we introduce an approximation sign function to turn the level set to the class label. In each local region, the locally linear function is fitted by a locally weighted squares energy. This energy is then integrated over the entire image domain to form 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 the object boundaries. Comparative experiments indicate that our algorithm has the following two main advantages:

1. Our model is a local region-based model, which shows high adaptability to images with intensity inhomogeneities. It assumes that the foreground and background is locally separable, which is more reasonable than the global separable constraint used in region-based methods. Compared with region-based methods, such as [23], the proposed method can yield higher segmentation accuracy, especially when image is inhomogeneous.
2. Theoretically, LBF and LGF, which use local mixture models to describe local region, can be regarded as generative model, while our LLC model, which adopts linear classification model, is actually a discriminative model. Generally, as discussed in object recognition area, discriminative model is more robust to model misspecification and has better performance at classification and regression tasks than generative model [35]. Besides, based on our locally linear classification, it is easy to introduce prior knowledge into our model, which will improve the robustness to the initial contour. As a result, our method is able to generate accurate segmentations with various initial contours. In practice, extensive experiments illustrate that our method is superior in terms of segmentation accuracy and initialization robustness.

A shorter version of this paper appeared in [36]. The current work is a extended one, including:

1. More details about the proposed approach related to theoretical derivations are introduced.
2. A detailed analysis about initialization robustness is presented.
3. More parameter settings related to the prior term for locally linear classification are introduced and evaluated via experiments.
4. Qualitative and quantitative evaluations are reported based on extensive comparison experiments.

The remainder of this paper is organized as follows. In Section 2, we review two classical 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. Background

In this section, we review two classical active contour models: the Chan–Vese (C–V) [17] model and the LBF model [30]. In the literature, the former is a popularly used region based method, while the latter is proven to be a typical local region-based model.

2.1. The C–V model

Chan and Vese [17] presented an active contour model based on a special case of Mumford–Shah functional. For an image I in image domain Ω, C–V model is proposed to minimize the following energy functional:

$$\mathcal{F}^{CV}(\mathcal{C},c_1,c_2)=\lambda_1\int_{\mathcal{C}_{\text{in}}}|I(\mathbf{x})-c_1|^2\,d\mathbf{x}+\lambda_2\int_{\mathcal{C}_{\text{out}}}|I(\mathbf{x})-c_2|^2\,d\mathbf{x}+\nu|\mathcal{C}|, \quad (1)$$

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

In level set method, the contour $\mathcal{C}$ is represented by the zero level set of a Lipschitz function ϕ. Let $\mathcal{C}=\{\mathbf{x}|\phi(\mathbf{x})=0,\mathbf{x}\in\Omega\}$, $\mathcal{C}_{\text{in}}=\{\mathbf{x}|\phi(\mathbf{x})>0,\mathbf{x}\in\Omega\}$ and $\mathcal{C}_{\text{out}}=\{\mathbf{x}|\phi(\mathbf{x})<0,\mathbf{x}\in\Omega\}$, then the above energy functional (1) can be converted to

$$\mathcal{F}^{CV}(\phi,c_1,c_2)=\lambda_1\int H(\phi(\mathbf{x}))|I(\mathbf{x})-c_1|^2\,d\mathbf{x} +\lambda_2\int(1-H(\phi(\mathbf{x})))|I(\mathbf{x})-c_2|^2\,d\mathbf{x} +\nu\int|\nabla H(\phi(\mathbf{x}))\,d\mathbf{x}, \quad (2)$$

where $H(\cdot)$ is the Heaviside step function. By minimizing the energy functional (2) in terms of c_1,c_2, we can solve c_1 and c_2 as follows:

$$c_1=\frac{\int H(\phi(\mathbf{x}))I(\mathbf{x})\,d\mathbf{x}}{\int H(\phi(\mathbf{x}))\,d\mathbf{x}}, \quad (3)$$

$$c_2=\frac{\int(1-H(\phi(\mathbf{x})))I(\mathbf{x})\,d\mathbf{x}}{\int(1-H(\phi(\mathbf{x})))\,d\mathbf{x}}. \quad (4)$$

Minimizing the energy functional (2) in terms of the level set function ϕ using the gradient descent method, we obtain the gradient descent flow

$$\frac{\partial\phi}{\partial t}=\delta(\phi)\left(-\lambda_1(I-c_1)^2+\lambda_2(I-c_2)^2+\operatorname{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right), \quad (5)$$

where $\delta(\cdot)$ is the Dirac delta function. Obviously, c_1 and c_2 can be viewed as the global cluster centers of the inside region $\mathcal{C}_{\text{in}}$ and $\mathcal{C}_{\text{out}}$, respectively. However, if the intensities in either $\mathcal{C}_{\text{in}}$ or $\mathcal{C}_{\text{out}}$ have multiple modes or if they are not homogeneous, only employing global cluster center c_i $(i=1,\ 2)$ is not enough to describe the region $\mathcal{C}_{\text{in}}$ and $\mathcal{C}_{\text{out}}$. Thus, the C–V model may fail to segment the images with intensity inhomogeneity.

2.2. The LBF model

To overcome the drawbacks of the C–V model, Li et al. [29,30] proposed a local region based model using intensity information in local regions. For a given point $\mathbf{x}\in\Omega$, a local fitting energy is defined as

$$\mathcal{E}^{\text{fit}}_{\mathbf{x}}(\phi,c_1(\mathbf{x}),c_2(\mathbf{x}))=\lambda_1\int K_\sigma(\mathbf{x}-\mathbf{y})H(\phi(\mathbf{y}))|I(\mathbf{y})-c_1(\mathbf{x})|^2\,d\mathbf{y} +\lambda_2\int K_\sigma(\mathbf{x}-\mathbf{y})(1-H(\phi(\mathbf{y})))|I(\mathbf{y})-c_2(\mathbf{x})|^2\,d\mathbf{y}, \quad (6)$$

where K_σ is the Gaussian kernel function (σ denotes its standard deviation σ) with a localization property that $K_\sigma(\mathbf{y}-\mathbf{x})$ decreases and approaches to zero as $\mathbf{y}$ goes way from the center point $\mathbf{x}$, $I(\mathbf{y})$ denotes the image intensity of point $\mathbf{y}$, and the fitting values $c_1(\mathbf{x})$ and $c_2(\mathbf{x})$ can be viewed as the weighted cluster centers of the image intensities in a Gaussian window around $\mathbf{x}$ inside and outside the contour, respectively. Combining the contour length energy term together, the total LBF energy functional in the image domain Ω is defined as follows:

$$\mathcal{E}^{\text{LBF}}(\phi,c_1,c_2)=\int\mathcal{E}^{\text{fit}}_{\mathbf{x}}(\phi,c_1(\mathbf{x}),c_2(\mathbf{x}))\,d\mathbf{x}+\nu\int|\nabla H(\phi(\mathbf{x}))|\,d\mathbf{x}. \quad (7)$$