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Local average fitting active contour model with thresholding for noisy image segmentation

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ABSTRACT

In this paper, an active contours model using neighborhood average fitting with thresholding is proposed for noisy images segmentation. Energy of the proposed model is formulated according to the difference between the local average and global region information. For images corrupted by noise, the neighborhood average method is capable of denoising at the expense of blurring images to some extent. However, problems that appear with average method can be settled by thresholding in this work. Minimization of the energy associated with the active contour model is then implemented in a variational level set framework. Moreover, to eliminate the need for costly re-initialization procedure, a reaction-diffusion method is adopted to regularize the level set function for stability. Experimental results on synthetic and real images validate the effectiveness of the proposed approach.

1. Introduction

During the acquisition process of images, noises often appear owing to the imperfect factors of equipment of image transmission and processing [1,2]. The advent of noises affects the quality of images, and hence brings about difficulties for images segmentation. Thus, a lot of effort is being spent on reducing noise so as to enhance images for post-processing such as segmentation and analysis [3].

There mainly exist two classes of methods for denoising: spatial filtering [4] and spectral filtering [5,6]. For spectral filtering, images should be converted into the frequency domain via Fourier transforms firstly. After the application of image processing, they should be transformed into spatial domain for recovery [6]. As for spatial filtering, image information is used for spatial transform directly. It is classified into either linear filter (average filter, Gaussian filter etc.) or non-linear filter (median filter etc.). Linear filter is good at reducing Gaussian noise, providing pretty good performance for other types of noises as well in most circumstance. Linear filter implements its functionality by summing all pixels within the sliding local window weightedly. Average filter, which owns simple algorithm and computational efficiency, is widely used in image denoising. However, when the noisy image is smoothed by average filtering, it would become blurred. This is due to the fact that, some details such as edges are smoothed as well. In particular, the lager the local neighborhood size is, the more blurred the image becomes. To settle with this problem, a threshold is introduced to decide whether the center pixel should be replaced. The basic idea lies in the absolute difference between the local intensity mean and given pixel's intensity: if it is larger than the threshold, then the given pixel is replaced by its local mean, otherwise, remains unchanged. In a word, the thresholding makes a tradeoff between noise suppression and feature preserving.

Image segmentation has always been one of the most important and challenging task in image processing and computer vision. Among the segmentation methods, active contours implemented via level set methods, have found applications in image segmentation successfully [7–10], owing to their flexible topological change. CV model [7], one of the most well-known region-based ones, assumes that the image intensities are statistically homogeneous in each region. It has been successfully used in various images with promising segmentations. Energy of CV model is formulated according to the difference between each pixel and the intensity mean of the corresponding region. When the image is corrupted by noise, CV model still exhibits good performance owing to its global independence. Nonetheless, when the image is corrupted by a significant amount of noise, it is less trivial to segment correctly. Hence, there is far too much noise to obtain a decent segmentation with CV model directly. Currently, many extensions of CV model have been proposed [11,12]. Yu incorporates the region fitting term to the DRLSE model [13] to obtain the R-DRLSE model [12], making for an improvement of robustness. Again, the similar problem is also encountered with R-DRLSE model. Liu presents an improved robust Chan–Vese (RCV) model for noisy image segmentation [11].

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In [11], for each point, the local energy is defined according to the difference between the intensities of all points within its neighborhood and the intensity mean of the region. The RCV model is robust to image noise while preserving the segmentation efficacy. All of these methods stated above work in most circumstance, but still have some drawbacks such as image smoothing [12] that can result in loss of important image details. Another drawback of classic CV model is the requirement of the computational re-initialization. To eliminate the re-initialization, many models have come into being [13–17]. Reaction-diffusion (RD) method proposed by Zhang has advantages [14] over the others [13,15], including weak boundary anti-leakage and robustness to noise etc.

Up to now, in light of kinds of problems, various filters have been embedded into the popular active contour model [8–10,16]. In [9,10], Gabor filter is integrated into active contour model for texture segmentation. Morphology filter is incorporated into the region-based deformable model to segment images with intensity inhomogeneity [8]. Zhang introduces Gaussian filter to smooth the level set function and eliminate the time-consuming re-initialization [16]. In [17], Gaussian filter is used to compute edge indicator in edge-based model, which could be replaced by the support value filter proposed in [18]. Usually, the filtering is incorporated in segmentation methods as pre- or post-processing. It plays a part in smoothing the image or regularizing 3-D surface. In this paper, we propose a local average fitting active contour model for noisy images segmentation. Different from CV model [7], energy of the proposed model is based on the local average and global region information, which behaves well in noisy image segmentation. However, as each pixel is replaced by its neighborhood average intensity, the proposed model would decrease its shape discrimination. Aimed at the problem that appears with average filtering, we introduce a threshold to decide whether the given pixel should be replaced. Then minimization of the energy associated with the active contour model is implemented in a level set framework. In addition, to eliminate the need for costly re-initialization procedure, a reaction-diffusion method is adopted to regularize the level set function for stability.

The rest of the paper is organized as follows. In Section 2 we review some related models briefly. Then, Section 3 devotes to the proposed model in this paper. Implement and experiment results are presented and analyzed in Section 4. This paper is summarized in Section 5.

2. Backgrounds

Let Ω be the image domain, and $I:\Omega\rightarrow\Re$ be a gray level image. x of the $I(x)$ is the pixel in Ω. The goal of image segmentation is to divide the image into disjoint subregions $\Omega_1, \ldots, \Omega_N$. On the basis of Mumford–Shah model [19], Chan and Vese propose an active contour model (i.e. CV model [7]), energy of which in term of level set function ϕ can be written as:

$$F^{CV} = \lambda_1 \int (I(x)-c_1)^2 H(\phi(x))dx + \lambda_2 \cdot \int (I(x)-c_2)^2 (1-H(\phi(x)))dx + \nu \int |\nabla H(\phi(x))| dx \qquad (1)$$

where $H(\phi(x))$ is Heaviside function which specifies the interior of zero level set function, and vice versa. c_1 and c_2 designate two constants that approximate the image intensities in interior and exterior of zero level set function, respectively. λ_1 and λ_2 are fixed constants. The third term computes the length of the zero level set function. For parameter $\nu \geq 0$, if we have not to detect smaller objects (like points, due to noise), ν has to be larger [7].

Minimizing the energy functional Eq. (1) in terms of the level set function ϕ using the gradient descent method, we obtain the gradient descent flow:

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

In [7], the level set function is re-initialized locally to the signed distance function, which leads to a computational burden. In recent years, some variational level set formulations which are free of re-initialization come forth [13–17]. [14] introduces a diffusion term into the conventional level set evolution (LSE) equation, adding a diffusion term $\gamma\Delta\phi$ into Eq. (2):

$$\frac{\partial \phi}{\partial t} = \gamma\Delta\phi - \frac{1}{\gamma}L(\phi) \qquad (3)$$

where γ is a small positive constant. The diffusion term $\gamma\Delta\phi$ gradually regularizes the level set function to be a piecewise constant in each region, and the reaction term $\gamma^{-1}L(\phi)$ forces the final stable solution of Eq. (3) to $L(\phi)=0$. More detailed explanation about the RD method can be seen in [14].

3. The proposed model

3.1. Local average with threshold feature

Let $f(x, y)$ be a noisy image to be processed. $g(x, y)$ denotes a smoothed image. Then, the process for image smooth by spatial filtering can be expressed as:

$$g(x,y) = f(x,y) * h(x,y) = \sum_{m,n\in N_S}\sum h(m,n) f(x-m, y-n) \qquad (4)$$

where * is the convolution operation. (m, n) is the pixel within the neighborhood N_S centered at the given point (x, y). $h(x, y)$ is the impulse response function of low pass filter. The neighborhood is a square window, which could be set to 3×3, 5×5 etc. For the 8-neighborhood with radius being $\sqrt{2}$, $h(x, y)$ is:

$$h(x,y) = \frac{1}{8}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

We demonstrate the effect of the average filtering by using a synthetic image of a machine object. The synthetic noisy image is added by severe Gaussian noise with mean 0 and variance 0.08 as shown in Fig. 1(b). At the locations from row 13 to 103 with column being 93 marked with white line in Fig. 1(a), the gray intensity of noisy image and average filtered image are plotted along with the intensity of original noise-free image as shown in Fig. 1(d). The smoothed image implemented by average filtering is shown in Fig. 1(c).

As can be seen from Fig. 1(b), the noise leads to a quite big difference between some pixel and its local neighborhood intensity. Also, we can observe from the green virtual line in Fig. 1(d), there is lots of wide intensity variation in both object and background. Thus it is difficult to implement segmentation methods to get accurate results directly. Then after the application of average filtering, the intensity of the smoothed image (the blue line in Fig. 1(d)) is consistent with that of the original image.

However, as can be observed from Fig. 1(c) and (d), the average filtering would blur the image. And the larger the neighborhood size is, the more blurred the smoothed image is. To alleviate the problems caused by filtering, we introduce thresholding technique to improve the filtering. The basic idea is to set a threshold firstly; then compute the absolute difference between the given pixel and its local neighborhood intensity mean; and finally compare it to the threshold value to decide whether a pixel should be replaced by its