Robust active contours for fast image segmentation

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A robust active contour model is proposed for fast image segmentation. By introducing the intensity fitting energy in a local region, the proposed model can segment the images with intensity inhomogeneity efficiently. Since the local fitting functions are computed before curve evolution, the proposed model is insensitive to initialisation and has a high segmentation efficiency. Experiments on several synthetic and real images have proved the effectiveness of the proposed model.

Introduction: Active contour models have been widely applied in the domain of image segmentation with desirable results since the presentation by Kass *et al.* [1]. Active contour models can be roughly categorised into two basic classes: one is edge-based models [2] and the other is region-based models [3–5]. Edge-based models often use an edge indicator to attract the curve to the target boundaries. However, for images with smooth and weak boundaries, it is difficult to segment precisely. Region-based models usually use a certain region descriptor to find a partition on the image domain. The C-V model, proposed by Chan and Vese [3], is one of the most popular region-based models, but it cannot efficiently segment the images with intensity inhomogeneity because it assumes that the intensities of image are statistically homogeneous. Li *et al.* [4] proposed a region scalable fitting (RSF) model, which introduces the local fitting energy by a scale parameter. It can segment the images with intensity inhomogeneity precisely and efficiently. However, if the initial contour is set inappropriately, the RSF model tends to be stuck in local minima due to the fact that the energy functional is non-convex. In addition, when the initial contour is largely far away from the real boundary of the object, the RSF model is time consuming. Zhang *et al.* [5] presented an active contour model driven by local image fitting energy. Its segmentation efficiency is higher because only two convolutions are computed in each iteration while there are at least four convolutions in the RSF model. However, the problem of initialisation is not solved, it means an improper initial contour will lead to a wrong segmentation. Considering that the energy functional of local fitting model is non-convex, Chan *et al.* [6] proposed a method of transforming non-convex function into convex function. Hence, it can overcome the drawback of sticking in local minima naturally, but the process of calculation is complicated.

In this Letter, we present a robust active contour model based on local intensity fitting energy for image segmentation. A local region is introduced and divided into two parts according to the average value of intensity. Then, the average of each part is calculated, and the results are used to replace the traditional fitting functions that locally approximate the image intensities on the two sides of the contour. Experiments on several synthetic and real images have proved that the proposed model can segment the images with intensity inhomogeneity precisely and efficiently, and be insensitive to initialisation, and has a high segmentation efficiency compared with the RSF model.

Proposed model: Let $\Omega \subset R^2$ be the image domain and $I(x)$: $\Omega \to R$ be a given grey image. We first define a square neighbourhood Ω_x centred at x with width r. Next, we compute the average value of image intensity in the Ω_x, denoted as

$$f_m(x) = \text{mean}[I(y)|y \in \Omega_x] \tag{1}$$

where *mean* represents the average value. According to the value of $f_m(x)$, the local region Ω_x can be divided into two parts Ω_s and Ω_l, defined by

$$\begin{cases} \Omega_s = \{y{:}I(y) < f_m(x)\} \cap \Omega_x \\ \Omega_l = \{y{:}I(y) > f_m(x)\} \cap \Omega_x \end{cases} \tag{2}$$

where Ω_s represents the region where $I(y)$ is smaller than $f_m(x)$ in the Ω_x. Moreover, Ω_l represents the region where $I(y)$ is larger than $f_m(x)$ in the Ω_x. Then, we calculate the average value of the two parts, denoted as $f_s(x)$ and $f_l(x)$, respectively

$$\begin{cases} f_s(x) = \text{mean}(I(y)|y \in \Omega_s) \\ f_l(x) = \text{mean}(I(y)|y \in \Omega_l) \end{cases} \tag{3}$$

For a certain point x and width r, the values of $f_s(x)$ and $f_l(x)$ can be computed directly according to (1)–(3). For example, Fig. 1 shows the regions Ω_x, Ω_s and Ω_l on the point x, and corresponding value of $f_m(x)$, $f_s(x)$ and $f_l(x)$. The red line divides Ω_x into Ω_s and Ω_l.

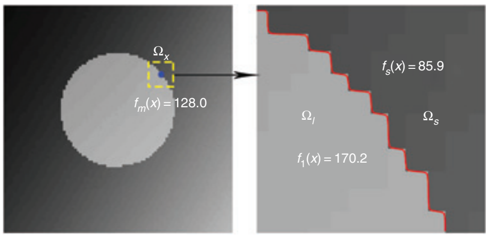

Fig. 1 *Illustration of regions Ω_x, Ω_s and Ω_l on point x, and corresponding value of $f_m(x)$, $f_s(x)$ and $f_l(x)$. Dashed yellow line denotes region Ω_x centred at blue point x. Red line denotes dividing line of Ω_s and Ω_l*

Then, we propose the following energy functional:

$$E(C) = \lambda_1 \int_{\text{outside}(C)} |I(x) - f_s(x)|^2 \,\text{d}x + \lambda_2 \int_{\text{inside}(C)} |I(x) - f_l(x)|^2 \,\text{d}x \tag{4}$$

where λ_1, λ_2 are constants. Here, $f_s(x)$ and $f_l(x)$ are defined in (3). When the above energy $E(C)$ is minimised, the curve C will locate on the boundary of the object.

Let the curve C be the zero level set of a Lipschitz function ϕ, above energy functional in (4) can be rewritten as

$$E(\phi) = \lambda_1 \int_\Omega |I(x) - f_s(x)|^2 H_\varepsilon(\phi) \,\text{d}x + \lambda_2 \int_\Omega |I(x) - f_l(x)|^2 [1 - H_\varepsilon(\phi)] \,\text{d}x \tag{5}$$

where $H_\varepsilon(\phi)$ is a Heaviside function approximated by a smooth function and $\delta_\varepsilon(x)$ is the derivative of $H_\varepsilon(\phi)$, defined as

$$\begin{cases} H_\varepsilon(x) = \dfrac{1}{2}\left(1 + \dfrac{2}{\pi}\arctan\left(\dfrac{x}{\varepsilon}\right)\right) \\ \delta_\varepsilon(x) = \dfrac{\varepsilon}{\pi(\varepsilon^2 + x^2)} \end{cases} \tag{6}$$

We add a distance regularised term $P(\phi)$ in [5] to free the re-initialisation and a length penalty term $L(\phi)$ to smooth the curve. Therefore, the entire energy functional $\mathscr{F}(\phi)$ can be expressed as

$$\mathcal{F}(\phi) = E(\phi) + \upsilon L(\phi) + \mu P(\phi) \tag{7}$$

where v and μ are the weight of length penalty term and distance regularised term, respectively. $L(\phi)$ and $P(\phi)$ are defined by

$$\begin{cases} L(\phi) = \int_\Omega \delta(\phi)|\nabla\phi(x)| \,\text{d}x \\ P(\phi) = \int_\Omega \dfrac{1}{2}[|\nabla\phi(x)| - 1]^2 \,\text{d}x \end{cases} \tag{8}$$

Minimising the energy functional in (7) with respect to ϕ by the method of steepest descent, the following gradient descent flow can be obtained:

$$\frac{\partial\phi}{\partial t} = -\delta_\varepsilon(\phi)[\lambda_1|I(x) - f_l(x)|^2 - \lambda_2|I(x) - f_s(x)|^2] + \upsilon\delta_\varepsilon(\phi)\,\text{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) + \mu\left(\nabla^2\phi - \text{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) \tag{9}$$

Since $f_s(x)$ and $f_l(x)$ are related to the image intensity in a local region whose size and shape are dependent on Ω_x, the proposed model can segment images with intensity inhomogeneity efficiently. In addition, $f_s(x)$ and $f_l(x)$ are computed before curve evolution and have nothing to do with level set function ϕ so that they do not need to update in each evolution. It is because $f_s(x)$ and $f_l(x)$ are fixed functions for a certain image that the proposed energy functional $\mathscr{F}(\phi)$ will not be trapped in local minima and has a fast evolution speed. Therefore, the proposed method has a very high segmentation efficiency and a good robustness of initialisation.

Experimental results: In this section, the proposed model will be tested with some synthetic and real images. The initial level set function ϕ_0 is initialised as a binary step function which takes −1 inside zero level set and 1 outside. Note that our model is not sensitive to the choice of the parameters. Unless otherwise specified, we use the following parameters in the proposed model: $r=13$, $\lambda_1=\lambda_2=1$, $\varepsilon=1$, $\mu=1$, $\upsilon=0.01\times 255^2$ and time step $\Delta t=0.1$. The proposed model is implemented in MATLAB R2014a on a 2.6 GHz Inter(R) Core(TM) i5 personal computer.

We first show the segmentation results of the proposed model for some images in Fig. 2. The process of curve evolution from the initial contour to the final contour is shown in every row for the corresponding image. The image in the first row of Fig. 2 is a synthetic image with intensity inhomogeneity. The second row shows a real tubal angiography image with quite weak edges and low contrast. In this experiment, the weight of length term $\upsilon=0.015\times 255^2$. The third row shows a real vessel image whose partial edges are weak and the background is severely inhomogeneous. The last row shows a synthetic image with non-uniform illumination and high-level noise. In this experiment, the width of neighbourhood $r=9$. All of the images in Fig. 2 are representative and challenging images with intensity inhomogeneity or weak edge. From the last column of Fig. 2, we can know that the desired segmentation results of these images have been obtained in our model. It proved that the proposed model is an efficient active contour model for image segmentation.

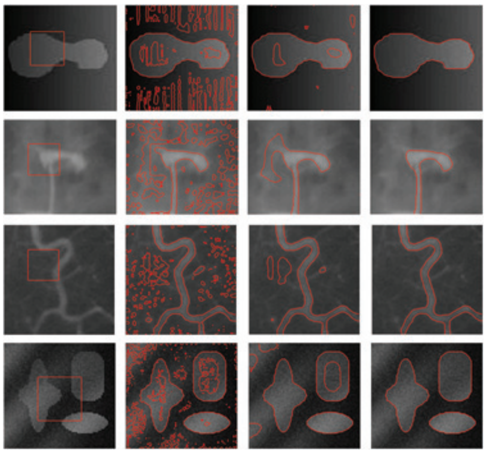

Fig. 2 *Results of proposed model for synthetic and real images. Every row represents process of curve evolution from initial contour (in first column) to final contour (in last column)*

Next, we will prove that the proposed model has a good robustness of initialisation and a high segmentation efficiency by comparing with the RSF model [4]. Take the first image in Fig. 2 for an example, we set four different positions of initial contour. In the RSF model, the weight of length term $\upsilon=0.002\times 255^2$, and other parameters are same to the proposed model, including the scale parameter. The segmentation results of the RSF model and the proposed model are shown in the upper row and lower row, respectively. The green line is initial contour and the red line is final contour.

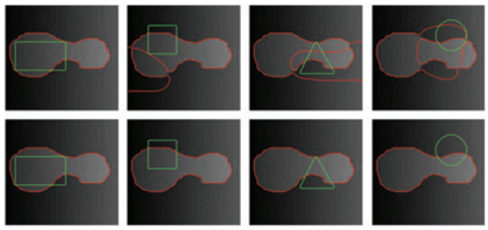

Fig. 3 *Comparisons between RSF model and proposed model with different positions of initial contour*

Upper row: Final results of RSF model
Lower row: Final results of proposed model

From Fig. 3, we can know that only the first case of initial contour obtains a correct segmentation result in the RSF model, and the number of iteration is 142, the time spent is 1.910 s. However, in the proposed model, each position of initial contour can obtain a correct result, and the number of iteration is 54, the time spent is 0.386 s in the first case. It fully proves that the proposed model is insensitive to the initialisation. Moreover, the proposed model has a higher segmentation efficiency than the RSF model. It means not only the number of iterations is less, but also the time of each iteration is shorter.

Conclusion: This Letter has presented a robust active contour model based on local intensity information for fast image segmentation. The proposed model is insensitive to initialisation and more efficient than the RSF model. In addition, the proposed model is applicable for noise image and can be extended to the colour image.

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One or more of the Figures in this Letter are available in colour online.

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