第 16 卷　第 8 期
2011 年 8 月

中国图象图形学报
Journal of Image and Graphics

Vol. 16, No. 8
Aug. , 2011

中图法分类号：TP391.41　　文献标志码：A　　文章编号：1006-8961(2011)08-1489-08
论文索引信息：田沄,周明全,段福庆,武仲科. 结合统计和梯度信息的高效活动轮廓模型[J]. 中国图象图形学报,2011,16(8)：1489-1496

Efficient active contour model driven by statistical and gradient information

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Abstract: A novel active contour model driven by statistical and gradient information is proposed in this paper. The model not only efficiently utilizes the gradient information of an object, which is in favor of fast and accurate location of boundaries, but also makes full use of the statistical information, including the global and local region information, which makes our method robust to noise. The use of the local region information makes the method free from intensity inhomogeneity of images, and the use of the global information helps to avoid the evolved contour trapping into local minima. Therefore, the initial contour can be set anywhere. Finally, the level set function is regularized by a Gaussian convolution kernel, which avoids an expensive computational re-initialization or regularization of the conventional models. Experimental results show that the proposed method can accurately and efficiently segment the homogenous images, as well as the inhomogenous images, with the initial contour set anywhere. Furthermore, the model is robust to noise.

Keywords: active contour model; statistical and gradient information; intensity inhomogeneity; Gaussian convolution; initial contour

结合统计和梯度信息的高效活动轮廓模型

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摘　要：提出一种由统计和梯度信息驱动的活动轮廓模型。该模型有效利用梯度信息使演化轮廓线快速精确地定位到物体的边缘;同时,由局部统计信息和全局统计信息构造符号压力函数,减少噪声对轮廓线演化的影响。另外,模型利用局部统计信息能够有效处理灰度分布不均的图像,全局信息的利用避免了演化轮廓线陷入局部最小,因此,该模型可以任意设置初始轮廓线。最后通过高斯卷积核对水平集函数规则化,避免了传统模型中计算代价高昂的重新初始化和规则化。实验结果表明,提出的模型不仅能够在任意初始轮廓下精确有效地分割灰度分布均匀的图像和不均匀的图像,而且对噪声具有较好的鲁棒性。

关键词：活动轮廓模型;统计和梯度信息;灰度分布不均匀;高斯卷积;初始轮廓线

0　Introduction

The active contour models, which are based on the theory of surface evolution and geometric flows, have been extensively studied and successfully used in image processing[1-5]. The models can achieve subpixel accuracy and provide closed and smooth contours or

收稿日期:2010-07-01;**修回日期**:2010-09-26
基金项目:国家自然科学基金重点项目(60736008);国家自然科学基金项目(61003134, 60872127);北京市自然科学基金重点项目(4081002)。
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surfaces, and the existing models can be categorized into two classes: edge-based models [1, 6-9] and region-based models [2-4, 10-11]. Edge-based models utilize image gradient to stop the evolving contours on the object boundaries. In these models, the geodesic active contours (GAC) is one of the most popular [9, 12], which consists of an edge-based stopping term and a balloon force term to control the motion of the contour. The edge-based stopping term serves to stop the contour on the desired object boundary. The balloon force term is introduced to expand or shrink the contour, yet it is sometimes difficult to design the appropriate balloon force. Region-based models utilize the image statistical information to construct constraints, and have some advantages over edge-based ones. Firstly, they do not use the image gradient, and are less sensitive to noise and have better performance for images with weak edges or without edges. Secondly, they are significantly less sensitive to the location of initial contours. One of the most popular region-based models is C-V model [2], which has been successfully used in binary phase segmentation with the assumption that image intensities are statistically homogeneous in each region, and thus fail to segment the image with intensity inhomogeneity. Aiming to this problem, local intensity information has been incorporated into the active contour models [13-19], For example, Li et al. [13-14] proposed a local binary fitting (LBF) model, Wang et al. [16] developed the LBF model, and Zhang et al. [17] proposed a local image fitting (LIF) model cooperating with Gaussian filtering to regularize the level set function. However, all these are sensitive to the initial contour, and only use local intensity information without the global and edge information.

Zhang et al. [18] developed the SBGFRLS (selective binary and Gaussian filtering regularized level set) model from the C-V and GAC models, and the model rarely utilizes the local region information and edge information. As a result, it is difficult to locate the exact location of the object's boundaries, and fails to handle the image with intensity inhomogeneity.

In this paper, we propose a novel active contour model that can segment the general images under the initial contour anywhere. Firstly, we utilize the local and global statistical information inside and outside the contour to construct a region-based SPF (signed pressure force) function. Secondly, the edge information is integrated in the model to assist guiding evolution of the contours accurately and efficiently. In addition, a regularization term, which speeds the propagation of contours, is added. Lastly, a Gaussian filtering is used to regularize the level set function after each iteration. Experiments demonstrate desirable performances of the proposed method.

The rest of the paper is organized as follows. In Section 2, we review some classic models. Section 3 describes our model and its numerical method. In Section 4, we validate our method by various experimentations on synthetic and real images. Conclusion is made in Section 5.

1 Background

1.1 The GAC model

Let $\boldsymbol{\Omega}$ be a boundary open subset of $\boldsymbol{R}^2$ and $\boldsymbol{I}$: $[0,a]\times[0,b]\to\boldsymbol{R}^+$ be a given image. Let $C(p):[0,1]\to\boldsymbol{R}^2$ be a parameterized planar curve in $\boldsymbol{\Omega}$. The GAC model is formulated by minimizing the following energy functional:

$$E(C(p)) = \int_0^1 g(C(p))\,|C_p(p)|\,\mathrm{d}p \tag{1}$$

where g is the edge stopping function (ESF). Usually, a positive decreasing and regular ESF is used that $\lim\limits_{t\to\infty} g(t) = 0$. Using calculation of variation, the Eulaer-Lagrange equation of Eq.(1) can be obtained as follows:

$$\frac{\partial C}{\partial t} = g(C)k\boldsymbol{N} - (\nabla g\cdot\boldsymbol{N}))\boldsymbol{N} \tag{2}$$

where k is the curvature of the contour and N is the inward normal to the curve. Usually, a constant velocity term is added to increase the propagation speed. As a result, the corresponding level set formulation is as follows:

$$\frac{\partial\phi}{\partial t} = g|\nabla\phi|\left(\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)+\alpha\right)+\nabla g\cdot\nabla\phi \tag{3}$$

where α is the balloon force, which controls the contour shrinking or expanding.

1.2 The SBGFRLS model

Zhang et al.[18] proposed the SBGFRLS model by defining a SPF function to substitute for the ESF in Eq. (3). The level set formulation of the model can be written as

$$\frac{\partial\phi}{\partial t} = spf(I(x))\left(\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)+\alpha\right)|\nabla\phi| + \nabla spf(I(x))\cdot\nabla\phi \quad x\in\Omega \tag{4}$$

where $spf(x)$ denotes SPF function, and it is constructed as follows:

$$spf(I(x)) = \frac{I(x)-(C_1+C_2)/2}{\max(|I(x)-(C_1+C_2)/2|)} \tag{5}$$

where C_1 and C_2 are two constants, which are the average intensities inside and outside the contour.

1.3 The LBF model

Li et al.[13-14] proposed the LBF model by embedding the local image information, and the model can efficiently and accurately segment the general scenario including the images with intensity inhomogeneities. The basic idea of the model is to introduce a kernel function to define an energy functional as follows:

$$E(C,f_1,f_2) = \lambda_1\int_\Omega\int_{in(C)}K(x-y)|I(y)-f_1(x)|^2\mathrm{d}y\mathrm{d}x + \lambda_2\int_\Omega\int_{out(C)}K(x-y)|I(y)-f_2(x)|^2\mathrm{d}y\mathrm{d}x \tag{6}$$

where λ_1 and λ_2 are positive constants, and K is a kernel function with a localization property that $K(x)$ decreases and approaches zero as $|x|$ increase, and f_1 and f_2 are defined as follows:

$$\begin{cases} f_1(x) = average(I\in(\{x\in\Omega|\phi(x)<0\}\cap O_k(x))) \\ f_2(x) = average(I\in(\{x\in\Omega|\phi(x)>0\}\cap O_k(x))) \end{cases} \tag{7}$$

where $O_k(x)$ denotes the small neighborhood of the point x. The energy Eq. (6) can be converted to an equivalent level set formulation:

$$E(C,f_1,f_2) = \lambda_1\int\left[\int K(x-y)|I(y)-f_1(x)|^2\times H(\phi(y))\mathrm{d}y\right]\mathrm{d}x + \lambda_2\int\left[\int K(x-y)|I(y)-f_2(x)|^2(1-H(\phi(y)))\mathrm{d}y\right]\mathrm{d}x \tag{8}$$

where H is the regularized Heaviside function. In order to ensure stable evolution of the level set function ϕ, a distance regularizing term is added to penalize the deviation of the level set function ϕ from a SDF. In addition, a length term of the zero level curve of ϕ is also used to regularize the zero level curve of ϕ. Finally, the total variational formulation can be written as (9), shown at the bottom of the next page where as the Dirac function $\delta(\phi)$ is the derivative of H, f_1 and f_2 can be obtained by

$$\begin{cases} f_1(x) = \dfrac{K_\sigma(x)*[H(\phi)I(x)]}{K_\sigma(x)*H(\phi)} \\ f_2(x) = \dfrac{K_\sigma(x)*[(1-H(\phi))I(x)]}{K_\sigma(x)*(1-H(\phi))} \end{cases} \tag{9}$$

2 The proposed model

The three above-mentioned models all have their pros and cons. The GAC model relies on the edge gradient information to drive the contour to evolve, and is sensitive to noise. In addition, the contours are prone to fall to local minimum when the initial contour is far from the desired object boundary. The SBGFRLS model replaces the ESF by the SPF that is constructed by the global region statistical information, which can reduce the noise impact to the evolvement contour to a certain extent. Furthermore, a Gaussian filter is employed to regularize the level set function, which speeds evolvement of the contour. However, the model does not utilize the local regions information, and completely abnegates the gradient information, as a result, it can not segment images accurately, especially images with intensity inhomogeneity. As for the LBF model using the local intensity information efficiently, it can segment images with intensity inhomogeneity, and has achieved promising results. However, the localization property introduced may lead to many local minima of the energy functional. Consequently, the result is more dependent on the initialization of contour. Moreover, the model is inefficient due to the complex computation for the regularization of the level set function.

2.1 The proposed model

Based on the above analysis and discussion, we well combine the advantages of the GAC model, the SBGFRLS model and the LBF model. Fortunately, such combination also avoids the disadvantages of these models. Then, we utilize the gradient information, the global statistical and local statistical information to define a novel energy functional as follows:

$$E(C(p)) = \int_0^1 g(C(p))\,|C_p(p)|\,\mathrm{d}p + \mu\int_0^1 spf(C(p))\,|C_p(p)|\,\mathrm{d}p \tag{10}$$

where μ denotes regularization coefficient. The gradient descent flow that minimizes Eq. (11) can be obtained as

$$\frac{\partial C}{\partial t} = g(C)k\boldsymbol{N} - (\nabla g\cdot\boldsymbol{N})\boldsymbol{N} + \mu(spf(C)k\boldsymbol{N} - (\nabla spf\cdot\boldsymbol{N})\boldsymbol{N}) \tag{11}$$

Similar to Eq. (4), the corresponding level set formulation can be written:

$$\frac{\partial\phi}{\partial t} = g\cdot\left(\mathrm{div}\frac{\nabla\phi}{|\nabla\phi|} + \alpha\right)\cdot|\nabla\phi| + \nabla g\cdot\nabla\phi + \mu\cdot spf\cdot\left(\mathrm{div}\frac{\nabla\phi}{|\nabla\phi|} + v\right)\cdot|\nabla\phi| + \mu\cdot\nabla spf\cdot\nabla\phi \tag{12}$$

where α and v are two constants, which can speed propagation of the contours.

2.2 The design of SPF function

We utilize the local region information and the global region information to construct the SPF function as (14), shown at the bottom of this page, where w is a weighting factor $(0\leqslant w\leqslant 1)$. When the images possess more details, or are corrupted by intensity inhomogeneity, the value parameter of w should be sufficiently small. Otherwise, it can be set up larger. $I^{LFI}(x)$ denotes the local fitted image of the point x, and it can be obtained by $I^{LFI}(x) = f_1H(\phi) + f_2(1 - H(\phi))$.

$$\frac{\partial\phi}{\partial t} = -\delta(\phi)\left(\lambda_1\int_\Omega K_\sigma(y-x)\,|I(x) - f_1(y)|^2\mathrm{d}y + \lambda_2\int_\Omega K_\sigma(y-x)\,|I(x) - f_2(y)|^2\mathrm{d}y\right) + v\,\delta(\phi)\times \mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) + \mu\left(\nabla^2\phi - \mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) \tag{13}$$

$$spf(x) = \left[w\cdot\left(I(x) - \frac{f_1(x)+f_2(x)}{2}\right) + (1-w)\cdot\left(I^{LFI}(x) - \frac{(C_1+C_2)}{2}\right)\right] \Big/ \left[\max w\cdot\left(I(x) - \frac{f_1(x)+f_2(x)}{2}\right) + (1-w)\cdot\left(I^{LFI}(x) - \frac{(C_1+C_2)}{2}\right)\right] \tag{14}$$

2.3 Implementation

In implementing the traditional level set methods, it is numerically necessary to keep the evolving level set function close to a SDF. Re-initialization can prevent the level set function ϕ from developing shocks, very sharp and /or flat shape during the evolution, which makes further computation highly inaccurate. However, many existing re-initialization methods have an undesirable side effect of moving the zero level set away from its original location. Moreover, re-initialization is a very expensive procedure. To solve these problems, we employ a Gaussian kernel to regularize the level set function [17-18]. In the conventional level set methods, the term $\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\cdot|\nabla\phi|$ is used to regularize the level set function ϕ. Since ϕ is SDF, and it satisfies $|\nabla\phi| = 1$. The regularized term can be viewed as the Laplacian of the level set function ϕ. The evolution of a function with its Laplacian is equivalent to a Gaussian kernel filtering the initial condition of the function. So we can further regularize the level set function through a Gaussian filter, thus the regularization term $\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\cdot|\nabla\phi|$ in Eq.(13), is unnecessary. At the same time, $\nabla spf\cdot\nabla\phi$ and $\nabla g\cdot\nabla\phi$ can also be removed, because the model utilizes the statistical information of regions, which has large capture range and capacity of anti-edge leakage. In addition, a regularization term is added to speed the propagation of contours. In the end, the level set formulation of the proposed model can be written as

$$\frac{\partial\phi}{\partial t} = \alpha\cdot g\cdot|\nabla\phi| + \beta\cdot spf\cdot|\nabla\phi| +$$

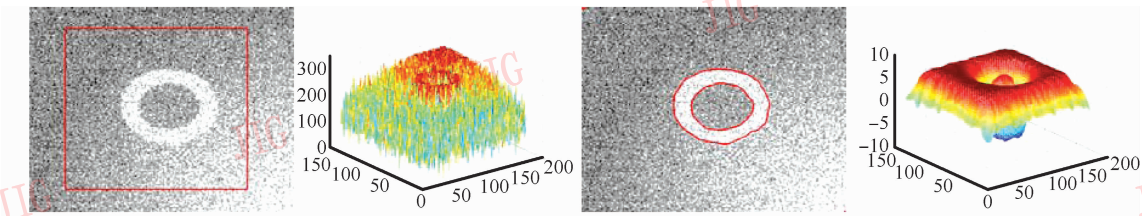
$$\lambda \cdot |\nabla \phi|^2 \tag{15}$$

where α, β and λ are three constants. In general, the parameter α can be set a large value when the edges of objects are more obvious. On the other hand, the parameter β can be chosen large enough if the images, especially their edges are rather unclear. The parameter λ can be chosen large enough if the contours to be further evolved.

3 Experimental results

The proposed method has been tested with different images, and the model is implemented by Matlab 7.0 on a computer with Intel (R) Pentium (R) Dual 2.0GHz CPU, 2.0G RAM and Windows XP operating systems. Unless otherwise specified, we use the following parameters in this paper: $\sigma_1 = 2.5$, $\sigma_2 = 2.5$, $K_2 = 5$, $\varepsilon = 2.0$, $\Delta t = 1.0$, $\lambda = 0$, and other parameters are set up by experience according to the images.

Firstly, we make an experiment with a noise circle image to which 15% Gaussian noise is added to validate the anti-noise performance of the proposed model. The noise image and its initial contour are shown in Fig. 1(a), and Fig. 1(b) shows the three-dimensional display of the image. For this image, we use the parameters $\sigma_1 = 4.0$, $\sigma_2 = 3.0$, $\varepsilon = 12.5$, $w = 0.01$, $\alpha = 6.5$, $\beta = -65$. Fig. 1(c) shows the final evolution contour, and Fig. 1(d) shows the final level set function. It can be seen from the final contour that the extracted boundaries are still fixed despite the large noise. However, it is worth noting that the global region weighting factor w is not equal to 0, but a small value 0.01. This is because little global information is used to guide or get on going evolvement of the contours to avoid trapping into local minima. This result demonstrates desirable performance of our method in extracting object boundaries in intensity inhomogeneity images with high noise.



(a) 15% Gaussian noise added to the image used in Fig. 1 and the initial contour　(b) three-dimensional display of (a)　(c) final contour after 170 iterations　(d) the final level set function of (c)

Fig. 1　Result of our method for the noise synthetic image

Secondly, we compare with the GAC model, LBF model, and the latest SBGFRLS model using an inhomogeneous image with a weak boundaries vessel. The first column of Fig. 2 shows both different initial contours with a circle. Among them, the first two contours do not intersect the vessel, and the third do intersect the vessel. The second column shows the corresponding evolved results of the GAC model, which demonstrates that the model can not handle the unclear image with the weak boundaries of objects. The corresponding results of the SBGFRLS model can be seen from the third column, which shows the model is stable no matter where the initial contour is Unfortunately, it can not achieve the desired boundaries due to the image intensity inhomogeneity and the weak boundaries of the blood vessel. The fourth column shows the evolved results of the LBF model. This model can accurately evolve the vessel boundaries when the initial contour is properly placed, which can be seen from the last row of the fourth column. However, the LBF model may obtain the undesired results if the initial contour does not intersect the vessel, which can be seen from the first two rows. This is mainly because the LBF model is based on the local region information. As a result, it is sensitive to the initial contour. In addition, the model is rather inefficient, and it spent about 20 minutes to achieve the shown perfect result. The last column shows the results of the proposed method, and it can be seen that the same result obtained under the three different initial contour situations, while it only cost about several seconds. Moreover, the satisfying segmentation results can be achieved, which are similar to the result shown in the second row by the LBF model.

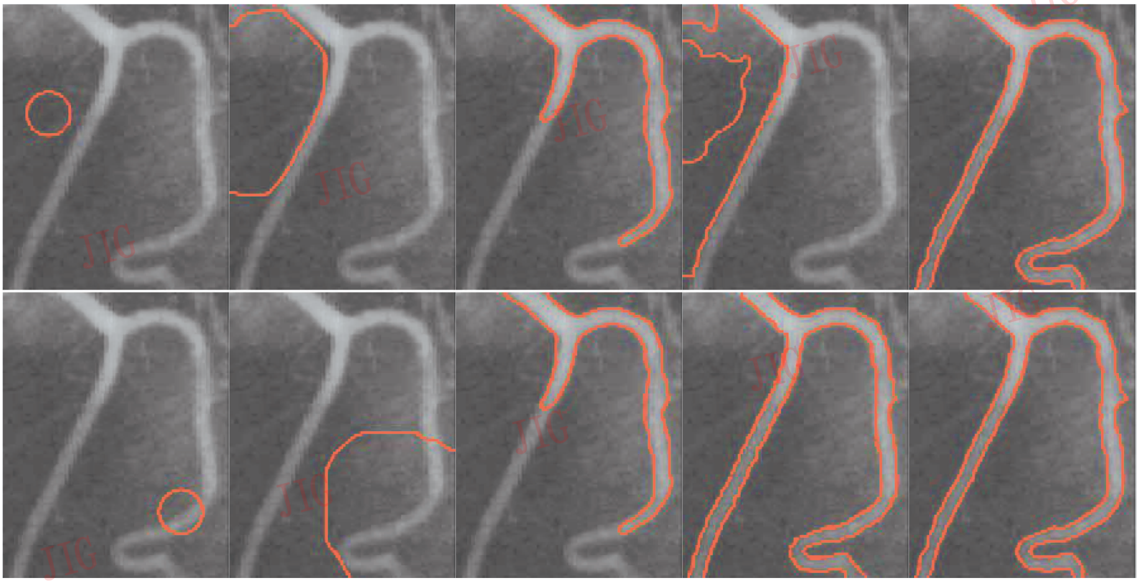


Fig. 2 Comparison of our method with the GAC, SBGFRLS and LBF models for a weak boundaries blood vessel image with intensity inhomogeneity. Column 1 shows the different initial contour shown in every row, and column 2, 3, 4 and 5 show the segmentation results of the GAC model, SBGFRLS model, LBF model and our method respectively. The corresponding parameters of our method with 120 iterations: $\sigma_2 = 2.0$, $\alpha = 0.5, \beta = 18, w = 0.1, \lambda = 0$

Fig. 3 shows the results of three real images, which are the 'T' image with 127 × 96 pixels, the brain MR image with 88 × 104 pixels and the heart image with 136 × 132 pixels, respectively. The segmentation results of the different methods are arranged as the same as Fig. 2. The undesired results in the second column are obtained by the GAC model. On the one hand, the model only makes use of very local information (like the snake model) and is very sensitive to local minima. On the other hand, due to the fact that the GAC framework relies on a non-parameterized curve, and evolves mainly an initial curve towards one direction (constrained by the curvature effect), it demands a specific initialization step, where the initial curve should be completely exterior or interior to the real object boundaries. The third column shows the segmentation results of the SBGFRLS model. For the homogeneous images, it can be seen from last two rows that the region of interest is coarsely segmented, however it is less accurate than that of the LBF model and the proposed method. For the 'T' image, the SBGFRLS model failed completely, which is imputed to the *spf* function of Eq. (5) deriving from the global region information. It guarantees the global optimization, yet ignores the local information. The fourth column shows the segmentation results of LBF model, the perfect result of the heart image is showed in the last row with the proper initial contour, while the result may be undesired when the initial contour is placed irrelevantly, which can be seen from the first row. The last column shows the results of the proposed method. Our model can successfully segment the objects of interest for the different images.

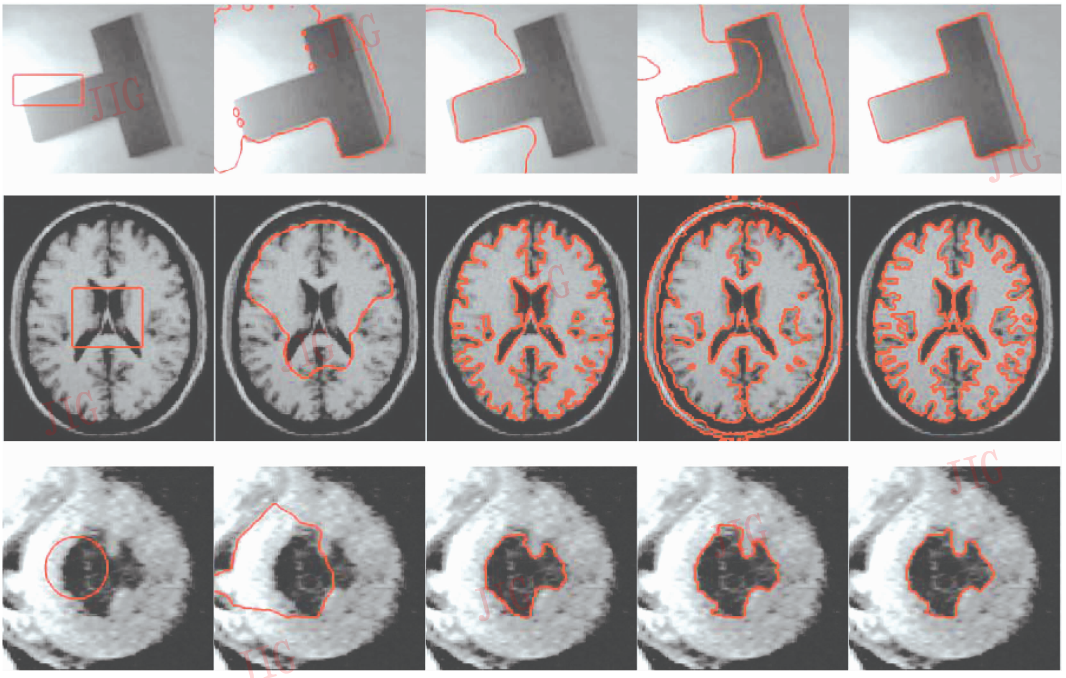


Fig. 3　Comparison of our method with the GAC, SBGFRLS and LBF models. Column 1 shows the initial contour for the different images, and column 2, 3, 4 and 5 show the segmentation results of the GAC model, SBGFRLS model, LBF model and our method respectively. The results of each image processed with different methods are shown in row

4　Conclusion

In this paper, we propose a novel active contour model for image segmentation, and its level set formulation is composed of three different term: a region-based term, a boundary-related term and a regularization term. The region-based term is constructed by the local and global statistical information inside and outside the evolvement contours, which is related to the direction and velocity of the contour propagation. The boundary-related term derives from the gradient information of images, which assists the contours evolving the edge of objects accurately and efficiently. The last term can speed the propagation of contours. Finally, the level set function is regularized by a Gaussian convolution kernel, which avoids an expensive computational re-initialization or regularization of the conventional models. The proposed model can process the general scenario including the image with intensity inhomogeneity under the initial contour set anywhere. Furthermore, the model is not only accurate and efficient, but also robust to noise. Experimental results demonstrate the desirable performances of the proposed model. However, the proposed model has some aspects to be improved, for example, requiring adjust ment of some parameters to adapt to different images. In addition, if some geometric shapes are taken into account, the evolvement result may be further improved.

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