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A Stable Image Segmentation Framework Using Gray and Contrast Guided Active Contour

Bo Cai[1,2*], Zhigui Liu[2,1], Junbo Wang[2,1] and Yuyu Zhu[2]

[1]*China Academy of Engineering Physics, Mianyang, Sichuan 621000, China*
[2]*Southwest University of Science & Technology, Mianyang Sichuan 621010, China*
caibo_bupt@126.com

Abstract

Image segmentation is a fundamental and challenging problem in image processing and often a vital step for high level analysis. Being CV based models have the unsatisfactory segmentation results and inefficient curve evolution against weak boundary and intensity heterogeneous images because of the inappropriate initial contour and unbalanced using the local and global information of the image. Based on the study of the edges and local/global contrast of the image, in this paper, we proposed a stable active contour model of image segmentation. Firstly, a new automatic initial contour choosing algorithm has been proposed which may improve the evolution efficient to a large extent compare to the human chosen initial contour. Besides, this algorithm may also improve the accuracy of the segmentation regions. Secondly, based on the study of the local binary fitting (LBF) model, local/global information fitting (LGIF) model and edge-flow based active contour model, we proposed a gray and contrast guided active contour model. In this model, we use gray and contrast information of the image as a decision standard to balance the local and global information. Finally, based on the above two algorithms, we construct a new image segmentation framework. The experiments show that our algorithm is less dependent on the parameters compare to the other models. On the other hand, this algorithm may also improve efficient of curve evolution to a large extent. Extensive experiments on synthetic and real images are provided to evaluate our method, showing the segmentation of the blurry boundary and intensity heterogeneous images may achieve more accuracy results.

***Keywords**: Image segmentation, CV model, Curve evolution, Initial contour, LBF, LGIF*

1. Introduction

Image segmentation as the subject of intensive research and a wide variety of segmentation techniques has been reported in recent decades. Active Contour Model (ACM) based segmentation algorithm has been widely investigated and applied to the image segmentation [1-8]. In general, the basic idea of active contour model is to deform an initial contour toward the actual boundary of the object. It may be categorized into edge-based[3, 9] and region based[1, 5, 6, 10, 11] models. In edge and region based ACM, image gradient and statistical information are often used to stop the contours respectively. The benefit of this kind of models is that the image has no global constraints, thus the objective and the background can be heterogeneous and the final segmentation can be achieved easily. However, it relies heavily on edge information of the input image, when an edge of the region is weak, such as blurred, or broken, the method may loss its roll.

Region-based active contour model (ACM) utilizes the objective and the background regions statistically and finds an energy optimum where the model best fits the image.

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Because of more advantages over edge-based ACMs, such as robustness for image with weak edges or without edges and insensitivity to the location of initial contours, region-based ACMs have been applied more popularly, in which, the Chan-Vese (CV) model[12] is one of the most popular region-based models. However, techniques that attempt to model regions using these kinds of methods are usually not ideal for segmenting heterogeneous objects, or transitional regions, which frequently occur in natural images.

There are many methods in the literat which are aimed at improving the segmentation accurate by introducing more edge or region information into the active contour model. Because of the minimization of the energy function heavily depends on the gray scale, the distribution and area of the image regions, the total information often leads to the false segmentation in the local region of the image. To overcome the problem of region non-homogeneous, Ge Qi et al[11] proposed a region based model with an anisotropic region fitting energy represented by a variational energy function. They introduced a struct tensor to define an anisotropic region fitting energy functional so that the intensity of an observed pixel is approximated through the intensity of its adjacent pixels at the principal directions. For the purpose of letting the active contour model more conform to the edges of the image region, Kovacs, Andrea et al[13] generates the main feat points based on the Harris corner detector, then these points are enveloped to get the initialization of the contour. Faced on the problems of intensity inhomogeneity, Yang, Yunyun et al[14] divide the fitting energy as local intensity fitting (LIF) energy and global intensity fitting (GIF) energy, and then use the two terms RSF model and CV model to realize the minimization of local-global intensity energy function. Since the external force plays a leading role in driving the active contour models, designing a novel external force field has been extensively studied [1, 5, 9, 10, 15]. Among all these external forces, gradient, edge, and gradient vector flow (GVF) has been used by Zhou Huiyu et al [16] as the outer driven force. In [9], Fang Lingling et al using the EdgeFlow-Based (EFB) active contour to realize the segmentation of the heterogeneous regions. Because of the edge of the regions is difficult to get, they use the Gaussian Mixt Model to realize the initial contour.

In this paper, we focus on the combining of the edge and region information in the evolution of active contour model. For the purpose of letting the region characterization be considered into the evolution, we use the region edge as the guided initial contour, and at the same time, the region information and local/global contrast are used in the evolution to control each evolution. The main advantages of our segmentation method can be highlighted as:

(1) Almost all the active contour models haven't give the analysis of the initial contour, in this paper we proposed a new algorithm to choose the initial contour which may improve the efficient of evolution to a large extent;

(2) Due to the initial contour is chosen according to the image contrast and edges, this makes the initial contour more adaptable to the input image characters;

(3) By adding the global reference into the local based active contour model, the proposed algorithm is more adaptable to the edge inhomogeneous and transitional regions.

The remainder of this paper is organized as follows. In section 2, we give a briefly review the local based and edge driven active contour models. The proposed model is introduced in section 3. In section 4, the initial contour choosing algorithm is introduced. Section 5 is the comparison of our model with LBF of segmentation results with different initial contour. We go on analyzing the results of the efficient and the convergence of each evolution. Finally, the conclusion and limitations of our model have been discussed in section 6.

2. The Review and Discussion of the Related Works

In this section, we give a review of the related active contour models based on Chan and Vese [12] model. For a given image $I(x)$ on the image domain R , Chan-Vese proposed to minimize the following energy equation:

$$E^{CV}(c_1, c_2, C) = \lambda_1 \int_{in(C)} \left| I(x) - c_1 \right|^2 dx + \lambda_2 \int_{out(C)} \left| I(x) - c_2 \right|^2 dx \qquad (1)$$

where c_1 and c_2 are two constants that approximate the average intensity inside and outside the curve, respectively. The coefficients λ_1 and λ_2 are fixed parameters.

By adding the regularizing term, such as the length of the contour and the area inside and outside the contour, the energy $E^{CV}(c_1, c_2, C)$ is defined as：

$$\begin{aligned} E^{CV}(c_1, c_2, C) = \lambda_1 \int_{in(C)} \left| I(x) - c_1 \right|^2 dx + \lambda_2 \int_{out(C)} \left| I(x) - c_2 \right|^2 dx \\ + \mu \mathrm{L}ength(C) + \nu Area\left(in(C)\right) \end{aligned} \qquad (2)$$

Using the level set to represent C , that is, C is the zero level set of Lipschitz function $\phi(x)$, the energy function may be rewritten as:

$$\begin{aligned} E^{CV}(c_1, c_2, \phi) = \lambda_1 \int_{\mathrm{R}} \left| I(x) - c_1 \right|^2 H\left(\phi(x)\right) dx + \lambda_2 \int_R \left| I(x) - c_2 \right|^2 \left(1 - H\left(\phi(x)\right)\right) dx \\ + \mu \int_R \delta\left(\phi(x)\right) \left| \nabla \phi(x) \right| dx + \nu \int_R H\left(\phi(x)\right) dx \end{aligned} \qquad (3)$$

where $H(\phi)$ and $\delta(\phi)$ are Heaviside function and Dirac function, respectively. The coefficients μ and ν are fixed parameters.

The CV model has a good performance on image segmentation due to its ability of obtaining a larger convergence range and being less sensitive to the initialization. However, the CV model is only adapted for 2-phase image. If the intensities with inside C or outside C are not homogeneous, the constants c_1 and c_2 will not be accurate. To overcome the difficult caused by intensity inhomogeneous, Li et al. proposed the local binary fitting (LBF) model[17], which can utilize the local intensity information. In the LBF model, two spatially varying fitting functions $f_1(x)$ and $f_2(x)$ are introduced to approximate the local intensities on the two sides of the contour, and for a given point $x \in R$, the local intensity fitting energy is defined by

$$\begin{aligned} E_x(C, f_1, f_2) = \lambda_1 \int_{in(C)} g(x - y)\left(I(y) - f_1(x)\right)^2 dy \\ + \lambda_2 \int_{out(C)} g(x - y)\left(I(v) - f_2(x)\right)^2 dy \end{aligned} \qquad (4)$$

where λ_1 and λ_2 are positive constants, $\mathrm{g}(y)$ is a Gaussian kernel function, and $f_1(x)$, $f_2(x)$ are two values that approximate image intensity inside and outside contour C , respectively.

The above local fitting energy $E_x(C, f_1, f_2)$ is defined for a center point x . For all the center point x in the image domain R , the energy function can be defined by

$$
\begin{aligned}
& E^{LBF}\left(C, f_1(x), f_2(x)\right) \\
& = \int_R E_x\left(C, f_1(x), f_2(x)\right) dx \\
& = \lambda_1 \int_R \left[\int_R g(x-y)\left(I(y) - f_1(x)\right)^2 H\left(\phi(y)\right) dy\right] dx \\
& + \lambda_2 \int_R \left[\int_R g(x-y)\left(I(v) - f_2(x)\right)^2 \left(1 - H\left(\phi(y)\right)\right) dy\right] dx
\end{aligned} \tag{5}
$$

Another way to deal with the intensity discontinuity is use the edge information as the factor of the ACM model. Fang et al. [18] define the energy function $x \in R$ as

$$
\begin{aligned}
& E_x^{EFB} = \int_{in(C)} g(y)\left|I(y) - c_1\right|^2 dy \\
& + \int_{out(C)} g(y)\left|I(y) - c_2\right|^2 dy + \lambda \int_R \delta_\varepsilon\left(\phi(x)\right)\left|\nabla \phi(x)\right| \\
& = \int_R g(y)\left|I(y) - c_1\right|^2 H_\varepsilon(\phi) dy \\
& + \int_R g(y)\left|I(y) - c_2\right|^2 \left(1 - H_\varepsilon(\phi)\right) dy \\
& + \lambda \int_R \delta_\varepsilon\left(\phi(x)\right)\left|\nabla \phi(x)\right|
\end{aligned} \tag{6}
$$

where $g(y)$ denotes Edge-Flow Based function: $g(y) = 1\Big/\left(1 + (y/k)^2\right)^m$, k is a contrast parameter separating low-contrast regions from high-contrast edges: $\mathrm{k} = 1.4826 \times median\left(\left\|y - median(y)\right\|\right)$. This selective processing enss that the image region is for $y < k$ and the image edge is for $y \geq \mathrm{k}$. Besides, m is a regulatory factor of Edge-Flow based function, which is used to achieving a better balance between keeping region edge and remove the noise near the edge.

Following this way, there are some papers aimed at dividing the local characters and the global characters of the image [3-5, 15, 19, 20], and constructing the energy function to solve the global and local problems. In this paper, we'll following the global and local problems of image segmentation. As stated in [18], the global contrast and local contrast is the key reference in human visual processing. Commonly, the high contrast of the image is related to the edge of the image regions. However, the edges are often exists in the different phase of image regions, and make the edges inhomogeneous in local regions. Simply sum the difference of all local regions may cause the global optimizing function result inconsistence to the local dividing results. On the other hand, only using the local dividing result to approximate the global segmentation may cause the wrong segment of the local regions.

3. The Proposed Model

In this paper, we will focus on the role of the image gradient and the global/local contrast in the active contour model (ACM) iteration. According to our experiments, the global mean c_1 and c_2 is the classification center of the image gray, and their value are mainly influenced by the total inner region pixels instead of the edge pixels. Comparing to the inner gray distribution, the contour is more easily influenced by the gray of the edge pixel. At the same time, because of the inhomogeneous of the region edges, the region edge may exist or not exist in the difference between c_1 and c_2 . When the edge-grays of the region are all less or higher than the global center c_1 and c_2 , the global dividing reference may lose its role.

Rough image **Dividing of rough image** **Initial contour** **Segmentation result**

Figure 1. The Proposed Image Segmentation Processing

3.1 The Local Binary Fitting Model

Given the input image $I(x)$ on the image domain R , LBF model use the region-based intensity information as a controllable scale in the energy model.

$$
\begin{aligned}
&E^{LBF}\left(C, f_1(x), f_2(x)\right) \\
&= \int_R E_x\left(C, f_1(x), f_2(x)\right)dx \\
&= \lambda_1 \int_R \left[\int_R g(x-y)\left(I(y)-f_1(x)\right)^2 H\left(\phi(y)\right)dy\right]dx \\
&+ \lambda_2 \int_R \left[\int_R g(x-y)\left(I(y)-f_2(x)\right)^2 \left(1-H\left(\phi(y)\right)\right)dy\right]dx
\end{aligned} \tag{7}
$$

The nonnegative weighted kernel function $g(x-y)$ is the Gaussian function $g(u)=\frac{1}{(2\pi)^{n/2}\sigma^n}e^{-|u|^2/2\sigma^2}$. Where $H(\phi)$ and $\delta(\phi)$ are Heaviside function and Dirac function respectively. Generally, the regularized versions are selected as

$$
\begin{aligned}
&H_\varepsilon(z)=\frac{1}{2}\left(1+\frac{2}{\pi}\arctan\left(\frac{z}{\varepsilon}\right)\right) \\
&\delta_\varepsilon(z)=\frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2+z^2}, \quad z \in R
\end{aligned} \tag{8}
$$

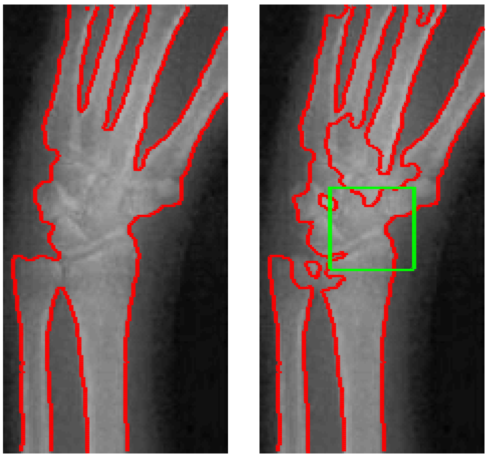
In LBF model, they keep the $\phi(x)$ fixed, and minimizing the energy $E^{LBF}(\phi, c_1, c_2)$ with respect to the constant $c_1 = f_1(x)$ and $c_2 = f_2(x)$ by using Euler-Lagrange equations. The calculation of c_1 and c_2 may be obtained:

$$\begin{cases} c_1(\phi) = \dfrac{\int_R g(x) * \left[I(x) H(\phi(x)) \right] dx}{\int_R g(x) * H(\phi(x)) dx} \\ c_2(\phi) = \dfrac{\int_R g(x) * \left[I(x)(1 - H(\phi(x))) \right] dx}{\int_R g(x) * (1 - H(\phi(x))) dx} \end{cases} \tag{9}$$

Here, c_1 and c_2 are the weighted means of the foreground and background of the image.

3.2. The Global Contrast Guided Algorithm

In LBF model, the weighted coefficient $g(x-y)$ is used to dispose the local characterization of the image. But the calculation of c_1 and c_2 is based on the evolutionary contour, the more homogeneous the inner region pixels the more quickly the edge would be achieved and at the same time the edge would be more accuracy. But, when the region edge is inhomogeneous or the region is transitional, this algorithm may leads to wrong segmentation especially on the blurred edges.



(a) (b)

Figure 2. The Correct Segmentation Result and the Segmentation Result of LBF (100times Iteration)

Seeing from the result of the LBF model in Figure 2, the local gray scale distribution may influence the evolution of LBF to the correct segmentation. And at the same time, the initial contour may cause the evolution wrongly dividing foreground and background in the local fitting processing. For the purpose of punishing the wrong segmentation, in the evolution processing, we use the global mean to divide the image into two parts, the downside gray and the upside gray. From Figure 3, we may found much of the edges are exist in the dividing by image mean, and the dividing is similar to segmentation result of the global based active model (LCV).

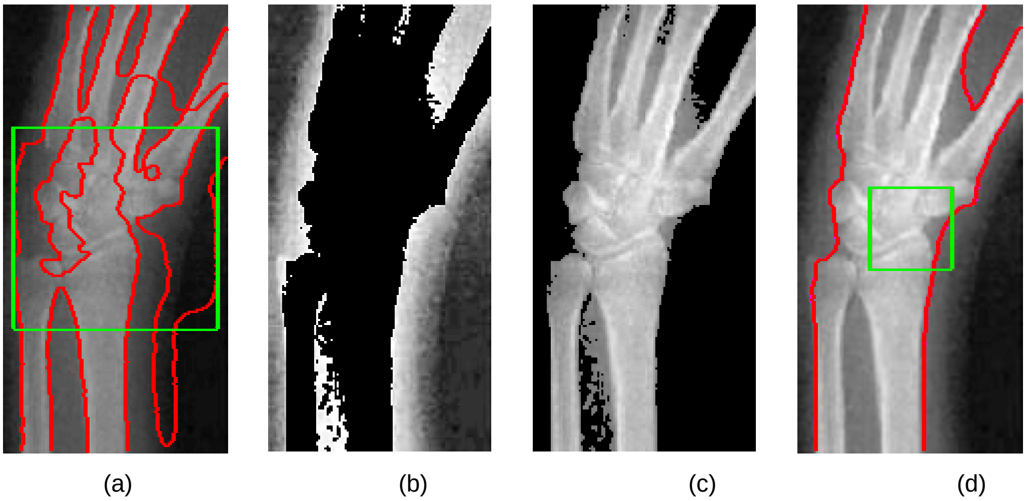


Figure 3. (A) Is The Evolution Result of LBF After 100 Times, (B) Is the Down Parts of the Image Gray, (C) Is the Upper Parts of the Image Gray, (D) Is the Segment Result of LCV

According to the above analysis, we choose the global contrast as the guide components to punish the false segmentation of local based active contour models. In this paper we choose the local binary fitting (LBF) model as the testing model. In Eq.7, the local fitting of background and foreground is decided by the local contrast of different sampling value of $I(y)$, $f_i(x)$ $i = 1,2$ and $g(x-y)$. When the local contrast is not consistent to the global contrast, the wrong segmentation may appear here. It's very difficult to decide whether the local segmentation or the global segmentation is right when there is not more information. Compare to the two results of Figure 3 (a) and (d), we found the local wrong segmentation may cause the total segment result much differs from the accurate result than the global model. Like the CV model, we use the mean dividing of the total image to punish the local dividing in each step of the evolution.

3.3. Level Set Formulation

In the level set based segmentation method, the segmentation contour C is represented as the zeroth level of a level set function ϕ. We focus on the homogeneous of the level set function ϕ by adding the weighted components of the global information. In such a case, when the cluster member is set to 2, the new level set ϕ', and the two class center c_1, c_2 may be calculated as:

$$\begin{cases} c_1'(\phi) = \dfrac{\int_R g(x) * \left[I(x) H(\phi'(x)) \right] dx}{\int_R g(x) * \left[H(\phi'(x)) \right] dx} \\ c_2'(\phi) = \dfrac{\int_R g(x) * \left[I(x)\left(1 - H(\phi'(x))\right) \right] dx}{\int_R g(x) * \left[\left(1 - H(\phi'(x))\right) \right] dx} \end{cases} \tag{10}$$

To preserve the regularity of the level set function ϕ, which is necessary for accurate computation and stable level set evolution, we introduce a level set regularization term in the variational level set formulation. The level set regularization term is defined as:

$$L(\phi) = \mu \int_R \left| H(\phi(x)) \right| dx \tag{11}$$

Adding the length term into the total energy function:

$$
\begin{aligned}
& E\left(C, c_1', c_2'\right) \\
& = \int_R E_x\left(C, c_1', c_2'\right) dx + \mu \int_R \left| H\left(\phi'(x)\right) \right| dx \\
& = \lambda_1 \int_R \left[\int_R g(x-y)\left(I(y)-c_1'\right)^2 H\left(\phi'(y)\right) dy \right] dx \\
& + \lambda_2 \int_R \left[\int_R g(x-y)\left(I(y)-c_2'\right)^2 \left(1 - H\left(\phi'(y)\right)\right) dy \right] dx \\
& + \mu \int_R \left| H\left(\phi'(x)\right) \right| dx
\end{aligned} \tag{12}
$$

where λ_1, λ_2 and u are the constant coefficient.

3.4. Optimization of the Model

For the purpose of letting region information guide the iteration, we divide the image into two parts, region inner area and region edge area. Before the calculation of the background mean and foreground mean, we use the directional mean value template to resample the region inner pixels of $\phi(x)$. After the resampling processing, we keep c_1' and c_2' fixed, and then to minimize the energy function $E(C, c_1', c_2')$. Parameterizing the descent direction by an artificial time t, we can obtain the corresponding variational level set function.

Keeping the clusters c_1' and c_2' fixed, the level set function is updated by solving the gradient flow equation:

$$
\phi^t = \phi^{t-1} - \eta \frac{dE\left(\phi, c_1', c_2'\right)}{d\phi} \tag{13}
$$

where η is the time step.

$$
\begin{aligned}
& \frac{\partial \phi'(x,t)}{\partial t} \\
& = \delta(\phi')\left[-\lambda_1\left(I(x)-c_1'\right)^2 + \lambda_2\left(I(x)-c_2'\right)^2 - \eta_1\left(I(x)-m_1'\right)^2 + \eta_2\left(I(x)-m_2'\right)^2 \right] \\
& + \delta(\phi')\left[\mu\, div\left(\frac{\nabla \phi'}{\left|\nabla \phi'\right|} \right) - \upsilon \right]
\end{aligned} \tag{14}
$$

where m_1' and m_2' is the mean of the up and down mean of the gray scale, η_1 and η_2 is the fixed coefficients (In all the following experiments, we choose $\eta_1 = \eta_2 = 0.0001$). When the local difference is smaller than the global difference, the value of $\lambda_i\left(I(y)-c_i'\right)^2 + \eta_i\left(I(y)-m_i'\right)^2$, $i = 1, 2$ is mainly controlled by the global dividing. On the contrary, the dividing is mainly influenced by the local information.

4. The Optimization of Initial Contour

Both edge-based model and region-based model have a fatal drawback: the position of the initial contour. The accurate position of initial contour can drastically reduce the time needed for segmentation. In general, the position of the initial contour is usually set manually. In this paper, we create a rough dividing of the image which close to the actually boundary using binary search algorithm.

As Figure 3 (b, c) shows, we roughly dividing the image accord to the mean value of the image gray, and choose the low ratio parts as the initial contour. According the above mentioned, the global based active contour is aimed at dividing the image into two classification, the evolution result is close to the mean dividing. Compare to the Gaussian Mixt Model [9], the mean dividing has less calculation, and at the same time when the distribution of the image gray scale is smooth, the Gaussian curve fitting may also lead to the wrong dividing in statistic.

5. Implementation and Experimental Results

In order to demonstrate the strengths of the proposed model, we perform different kinds of experiments. First of all, we compare the proposed model segment results with the other local based ACM model such as LBF without the proposed initial contour algorithm. Secondly, we continue with the properties of the proposed model with proposed initial contour, and give the comparison of the convergence with LBF. Finally, we extend the experiments with various images and noise.

5.1. Comparison with Other Local Based ACM Models

Commonly, the accurate choosing of initial contour is an important part in the process of image segmentation. For the purpose of compare the ability of the proposed model and the local binary fitting model, we choose the different initial contour of the same image. In these experiments, we let the parameter σ of Gaussian sampling function as fixed value 4 in all the iteration processing. Figure 4 shows the results of our model and LBF model. All the results are after 300 time iteration

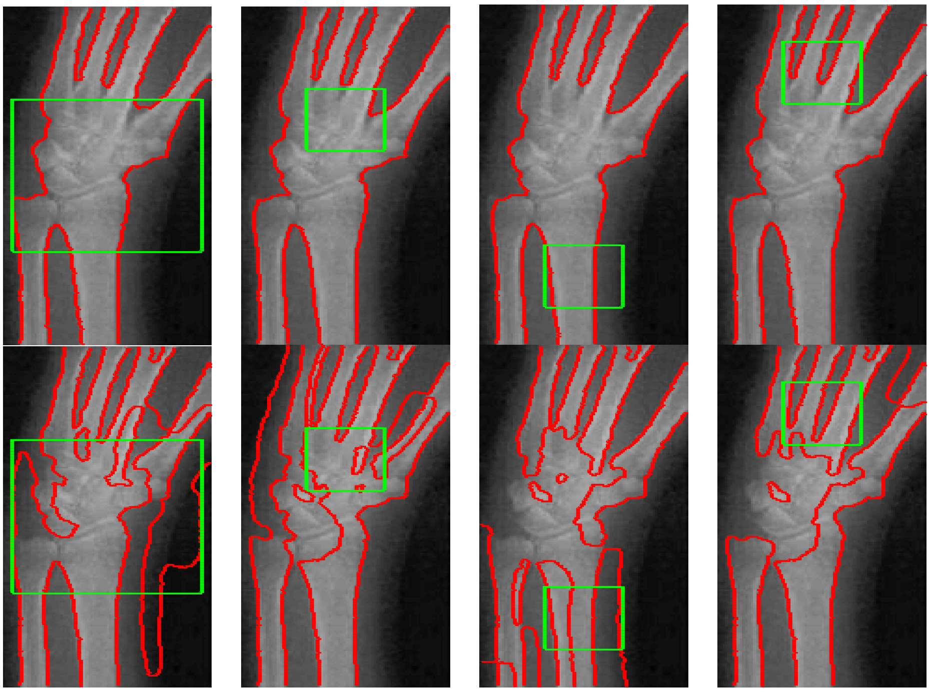


Figure 4. The Iteration Results of the Proposed Model and LBF, the First Row is the Results of Our Proposed Algorithm, the Second Row is the Result of LBF with Different Initial Contour

On the other hand, we also compared the results of different images. Figure 5 shows the results of different images. Seeing from comparative results of Figure 4, we may found the results of the proposed model is more close to the human visual result than the results of LBF. Because of the segment region of the testing image has different phase in gray scale, only using the local information may cause the local information different from the global information, and at the same time, the wrong results appeared. There are some details must be stated here, in the comparison of LBF and our model, the parameter σ has been set as a fixed value 4 , when the sigma is set to be 8, the result of LBF may be better than the presented results. But the choosing of the parameter is also mattering. Because of our purpose is to avoiding this problem in the total processing of image segmentation, so we set the parameter as a fixed value which is more adaptable for much of the two or nearly two phase images.

5.2. The Comparison of the Proposed Initial Contour

In this section, we give a comparison of our proposed initial contour and the human chosen initial contour. As the above mentioned, in the experiments of this part, we also let the parameter σ of Gaussian sampling function be the fixed value 4 . Figure 6 shows the results of different images.

The different initial contour may leads to different segmentation result, so the comparing of the result becomes very difficult. Based on our initial contour, the segment results are close to each other. On this condition, we give comparison of the different result of with global information and without global information. Figure 7 shows the difference of these two algorithms. When the global information is used, the blur edges of the region has a common segmentation ratio of segment the low and high gray scale, on the contrary, the LBF algorithm segment the blur edges only according to the local gray scale ratio or contrast.

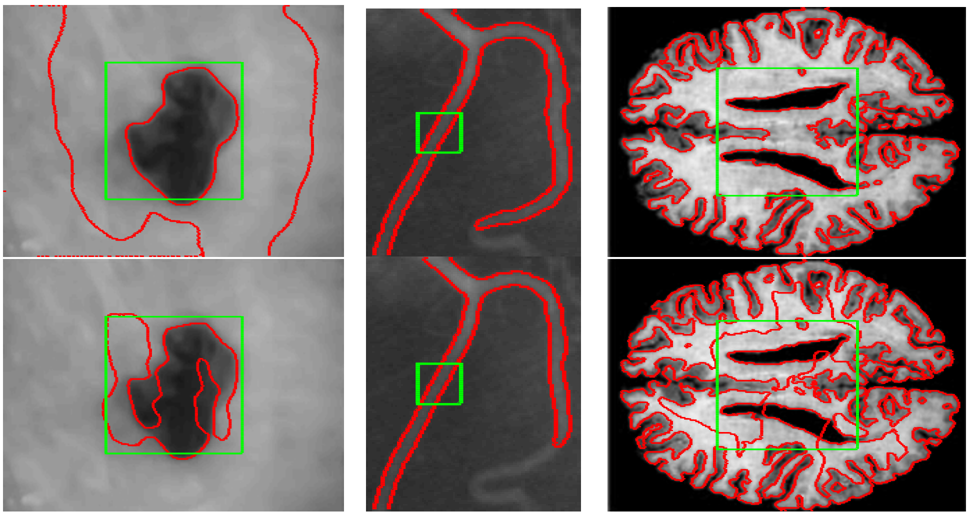
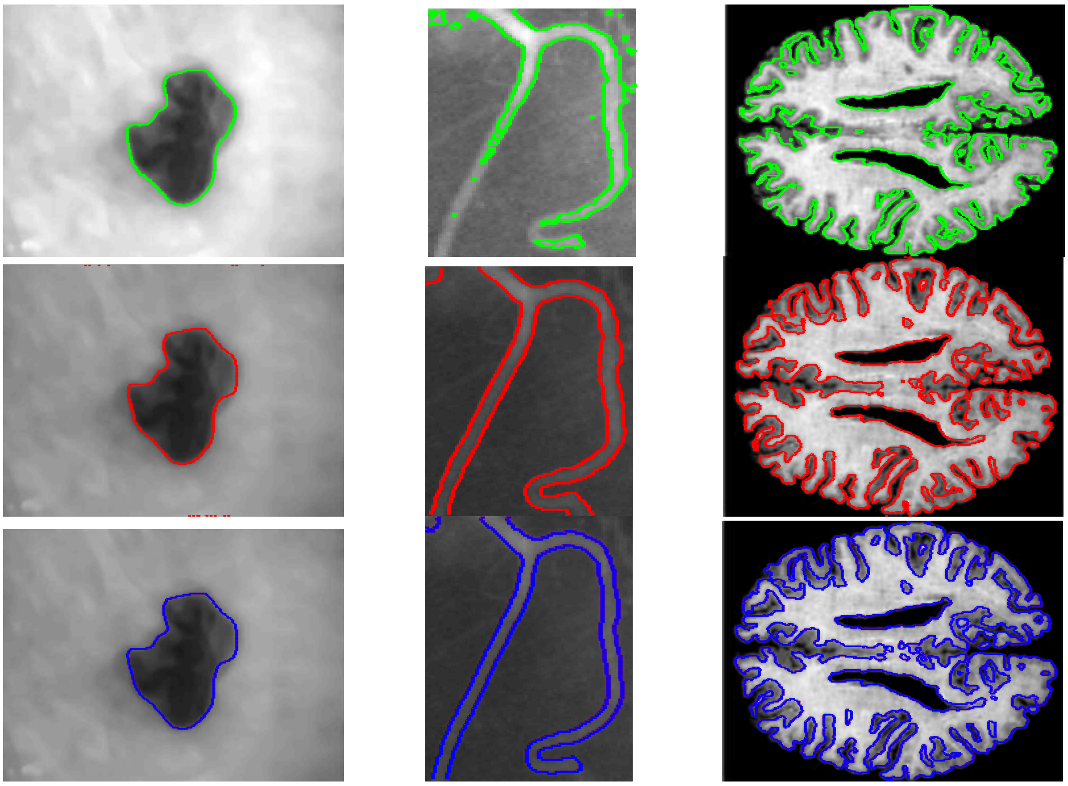
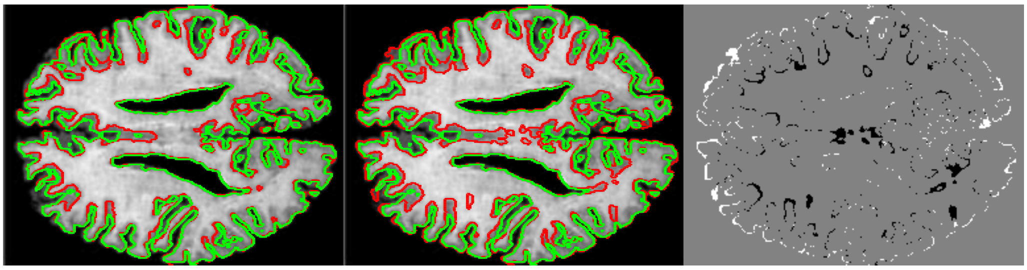


Figure 5 The Iteration Results of the Proposed Model and LBF with Different Images, The First Row is the Results of Our Proposed Algorithm, The Second Row is the Result of LBF



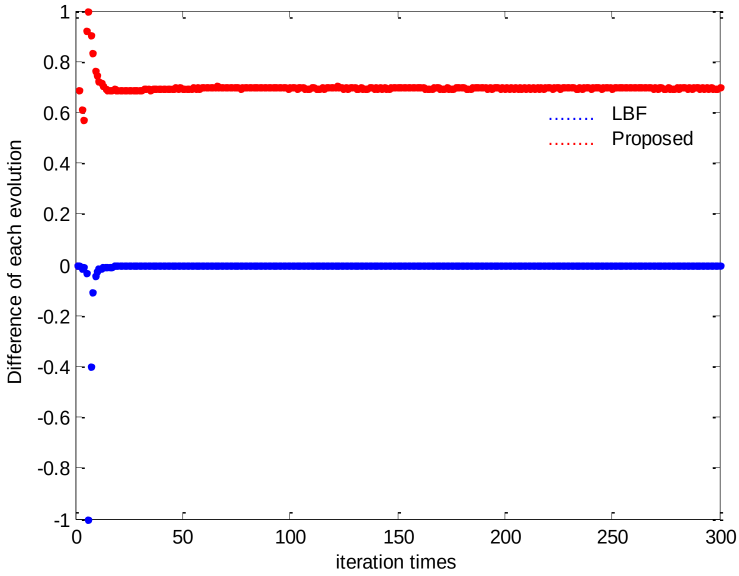
(a) (b) (c)

Figure 6. The Segment Result with and without the Global Information of The Proposed Model, The First Row is the Proposed Initial Contour, The Second Row is the Result of our Model and the Last Row is the Result of Lbf

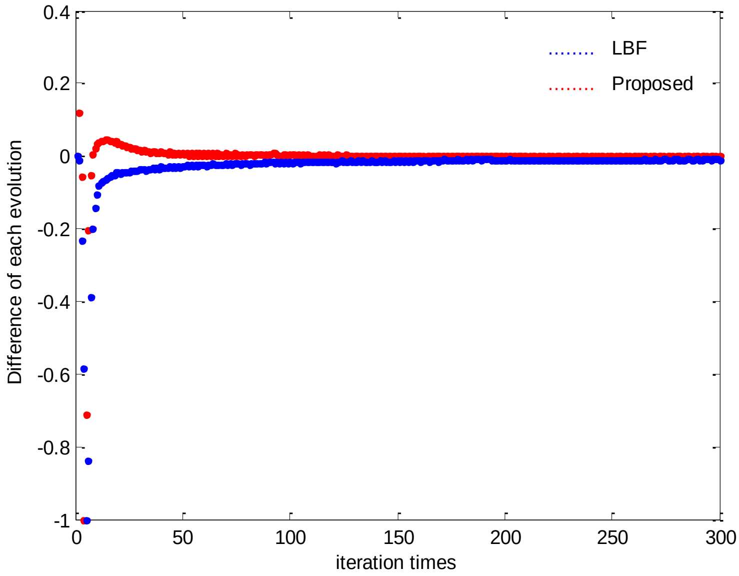


(a) (b) (c)

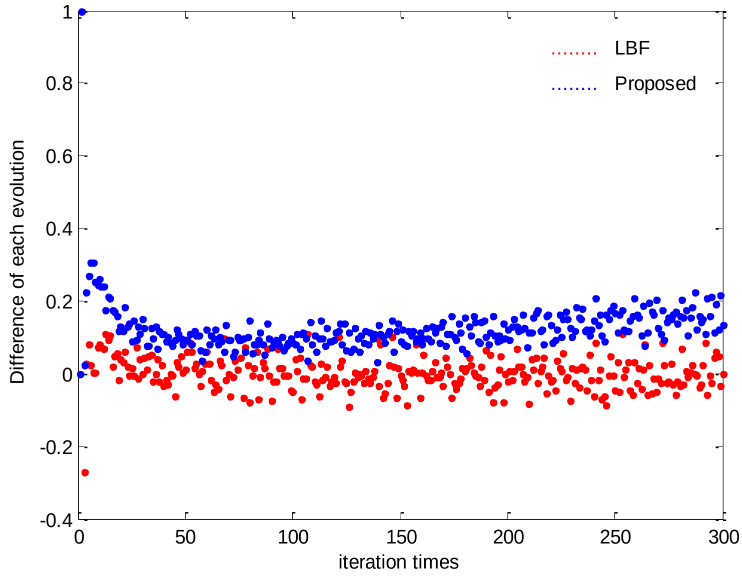
Figure 7. The Segment Result with and without the Global Information of the Proposed Model, (A) Is the Segment Result with Global Inform, (B) Is the Result of LBF, and (C) Is the Difference of these Two Algorithms



(a) the Iteration Processing of Figure 6(a)



(b) the Iteration Processing of Figure 6(b)



(c) the Iteration Processing of Figure 6(c)

Figure 8. The Comparison of the Convergence Processing of Figure 6 Images

Figure 8 shows the comparison of the convergence processing of Figure 6 (a-c). Seeing from the iteration difference of the three images, we may found when the background of the input image is homogeneous or near to the edge difference, the convergence processing and the results have less difference as (b) of Figure 8. When the background is inhomogeneous, the convergence results may different from each other, as shown in (a) of Figure 8. When the edge image region has more details, the convergence may vibrate in a scale as shown in Figure 8(c).

6. Conclusion

In this work, we propose a novel framework based on active contour model for image segmentation. The proposed model may efficiently utilize image global information and region information, which in certain case has resulted in significant improvement in accuracy and time consuming. Based on the problem of initial contour, we give some adjustments of initial contour to avoid the human choosing processing of active contour model.

For the purpose of make the segmentation result more accurate and efficient, we added the global information in the iteration processing. This may avoid the wrong segmentation of local regions to some extents. At the same time, this algorithm is adaptable to different images without adjusting the parameters and initial contour. In our algorithm, the initial contour is chosen by the mean value of the image gray. This dividing may cause some detailed initial contours, when the image foreground and background is very near, the segmentation results may have some little regions. In the following works, we will aim at finding the more stable initial contour.

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Authors

Bo Cai received his B.S. degree in mechatronics from China Agricultural University, in 1998, and M.S degree in Beijing University of Posts and Telecommunications, in 2003. Currently, he is the Ph.D candidate of China Academy of Engineering Physics. His research interests include image processing and detection.

Zhigui Liu received the Ph.D degree in traffic information engineering and control from Southwest Jiao Tong University, China, in 2006. Currently, he is the teacher of Southwest University of Science & Technology, and Ph. D tutor of China Academy of Engineering Physics. His research interests include vision sensor technology, image processing and machine vision, etc.

Junbo Wang received his B.S. degree in physics from Sichuan Normal University, China, in 1981, and the Ph.D degree in optical engineering from Chengdu electronic science and technology University, China, in 1985. Currently, he is the teacher of Southwest University of Science & Technology, and Ph. D tutor of China Academy of Engineering Physics. His research interests include atmospheric optical and detection, etc.

Yuyu Zhu received his B.S. degree in automation from Southwest University of Science & Technology, in 2002, and M.S degree in control engineering and control theory, in 2009. Currently, he is the teacher of Southwest University of Science & Technology. His research interests include signal detection and processing, power designing etc.