Active Contours Driven by Local and Global Region-Based Information for Image Segmentation

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ABSTRACT Intensity inhomogeneity and noise are two major parts in image segmentation. Aiming at these problems, this work proposes a novel hybrid active contour method which combines local and global statistical information into an improved signed pressure force (SPF) function. First, by considering the global information extracted from a region of interest, a new global-based SPF function is created that effectively adjusts the signs of the pressure force inside and outside the evolving curve. Second, a new local-based SPF function utilizes the normalized local intensity differences as the coefficients of local internal and external regions, which can segment complicated areas easily. Third, by combing the global-based SPF and the local-based SPF functions, an improved hybrid SPF function is constructed based on active contour approach. Experiments on many kinds of real and synthetic images show that our method makes superior segmentation accuracy and is more robust to initial contour and noises.

INDEX TERMS Active contour, image segmentation, signed pressure force, level set.

I. INTRODUCTION

Image segmentation is an important subject in related field of computer image analysis, image identification, object detection and other aspects [1]–[6]. The aim of segmentation is to separate a given image into different non-intersecting regions with specific properties such as intensities, colors and textures. Due to the intensity inhomogeneity, noise, and obscured boundaries, it still makes a lot of errors in the process of image segmentation. Over the past decades, extensive techniques have been developed. Among the available schemes, active contour methods based on evolution curves are wide application. Based on different image information, these models may be classified into edge-based [7]–[11] and region-based [12]–[16].

Edge-based methods rely on image edge information to detect target boundaries. Due to the local limitation, these models are quite dependent on contour curves. By employing region statistical information, region-based approaches often surpass edge-based models in terms of visual perception and poor edges. Among them, the Chan–Vese model (C-V) [17] is one of the most famous region-based models. By only considers global information, it would leads to poor segmentation performance when images have serious intensity inhomogeneity. In [18], Li et al. presented a classical region-scalable fitting (RSF) energy, which utilizes a convolution to compute the local region energy. Therefore, the RSF model can effectively suppress the influence of intensity inhomogeneity, but it is very dependent on the level set initialization and prone to trapped in a local minimum. Similarly, in [19], Min et al. proposed a novel image processing method based on multi-scale local feature. By using the proposed local maximum description difference feature, the optimal scale parameters for each local region is selected in an self-adaptive and the problems caused by intensity inhomogeneity can be effectively solved. In [20], Ma et al. proposed a novel local fitting algorithm, which utilized both local fitting term and regularization term to prompt the evolving
curve to the target edge. Different from the traditional active contour models, this approach utilizes local intensity variances to approximate the original image, so as to get a better solution. In [21], Li et al. proposed a new method to describe the features of the image region by using local prior region information through the Bayesian criteria. According to Bayesian theory, the connectivity graph improves noise robustness by bridging the relation between each pixel and its neighborhood pixels by using the Markov random field.

In order to make full use of the strength of the above-mentioned models, many hybrid level set algorithms integrating the local and global region information were presented to improve the segmentation quality. In [22], Fang et al. presented an improved level set algorithm that integrates global and local region information for segmenting US images. Results demonstrate that model can handle images with noise and fuzzy edges. In [23], Yuan et al. presented a novel level set framework to extract irregular shape targets from background polluted by noise and high intensity non-uniformity. By combining the global region information and local region information with a regularization term, this method is independent on the initial position of the evolving curve. In [24], Zhao et al. presented a robust segmentation algorithm in variational level set formulation. By subtracting the Gaussian blur image from the original image and replacing the original image with the image edge mapping, the model has good segmentation performance under the condition of low contrast and weak edges. In [25], by constructing two fitting images that approximate the original image and the square of original image, Li et al. proposed an energy functional, which can effectively prompt the active contour approximate to the target edge. In [26], Cai et al. presented a new approach for extract objects with intensity inhomogeneity. By defining an adaptive weighting term based on relative entropy to automatically modulation the coefficient between local and global energies, the method can effectively improve the processing speed.

Based on the above analysis, we present a new energy formulation that combination of local and global fitting terms. First, we use both local and global image intensity information to build the global weighted SPF and the local weighted SPF functions. The local information helps extract targets from intensity inhomogeneity, whereas the global information can accurately adjust the signs of the pressure forces internal and external of the evolving curve. Then, a weight function is established to modulate the rate between the above two SPF functions. Experimental results demonstrate that our method makes superior segmentation accuracy and robustness.

The arrangements are organized as follows: Section 2 briefly introduces the relevant work. In Section 3, we describe the energy functional of our model. The experimental results and discussion are provided in Section 4, and finally concluding statements are listed in Section 5.

II. RELATED WORK

A. C-V MODEL

The Chan–Vese method (C-V) [17] proposed by Chan and Vese, it assumes that objects of segmenting images are homogeneous. Let \( I : \Omega \rightarrow R^2 \) be the original image, \( C \) is an arbitrary curve. Thus, the external energy of C-V is constructed as:

\[
E^{CV}(C, c_1, c_2) = v \text{Area}(\text{inside}(C)) + \mu \text{Length}(C) + \lambda_1 \int_{\text{inside}(C)} |I(x) - c_1|^2 dx + \lambda_2 \int_{\text{outside}(C)} |I(x) - c_2|^2 dx \tag{1}
\]

where \( \lambda_1, \lambda_2, \nu, \mu \) show the related coefficients, \( c_1 \) and \( c_2 \) represent the average gray value inside and outside of \( C \).

To minimize the energy function (1), the curve \( C \) is described by the zero LSF. Then, the energy function can be converted:

\[
E^{CV}(\phi, c_1, c_2) = v \int_{\Omega} H_{c}(\phi) dx + \mu \int_{\Omega} \delta_{c}(\phi) |\nabla \phi| dx + \lambda_1 \int_{\Omega} |I(x) - c_1|^{2} H_{c}(\phi) dx + \lambda_2 \int_{\Omega} |I(x) - c_2|^{2}(1 - H_{c}(\phi)) dx \tag{2}
\]

where \( \varepsilon \) is a corresponding constant, \( H_{c} \) is the Heaviside function defined as:

\[
H_{c}(x) = \frac{1}{2} \left[ 1 + \frac{2}{\pi} \arctan \left( \frac{X}{\varepsilon} \right) \right] \tag{3}
\]

The derivative of \( H_{c} \) is defined by:

\[
\delta_{c}(x) = H'_{c}(x) = \frac{1}{\pi \varepsilon^{2} + x^{2}} \tag{4}
\]

According to the calculus of variations, we can get the following formula:

\[
\frac{\partial \phi}{\partial t} = \delta(\phi)[v \text{div}(\nabla \phi) - \lambda_1 |I(x) - c_1|^{2} + \lambda_2 |I(x) - c_2|^{2}] \tag{5}
\]

with \( c_1 \) and \( c_2 \) equal to

\[
c_1 = \frac{\int_{\Omega} H_{c}(\phi)I(x) dx}{\int_{\Omega} H_{c}(\phi) dx}, \quad c_2 = \frac{\int_{\Omega} (1 - H_{c}(\phi))I(x) dx}{\int_{\Omega}(1 - H_{c}(\phi)) dx} \tag{6}
\]

The C-V model is based on the precondition that target and background in an image are statistically homogeneous. However, if the intensities of image are in large variance, it would leads to poor segmentation performance.

B. SBGFRLS MODEL

In [27], Zhang et al. presented a new region-based method driven by the SPF to deal with image, which has the characteristics of both GAC [28] and C-V [17]. It utilizes the average
intensities of the internal and external of the region of interest, which can control the evolutionary direction. Therefore, the SPF equation can be obtained by:

$$\text{spf}(I(x)) = \frac{I(x) - \frac{c_1 + c_2}{2}}{\max(|I(x) - \frac{c_1 + c_2}{2}|)}$$ (7)

On the above basis, the SPF is used to substitute the edge detector function in the GAC algorithm and thus the level set formula of SBGFRLS can be expressed as:

$$\frac{\partial \phi}{\partial t} = \text{spf}(I(x)) \left[ \mathbf{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) + \alpha \right] |\nabla \phi| + \nabla \text{spf}(I(x)) \cdot \nabla \phi$$ (8)

In order to decline the calculation cost, some unnecessary terms can be removed. Finally, (8) is simplified as:

$$\frac{\partial \phi}{\partial t} = \text{spf}(I(x)) |\nabla \phi|$$ (9)

The SBGFRLS model mainly relies on the difference of image intensity and fitting intensity between the region inside and outside the evolution curve. However, when facing heterogeneous intensity distributions, its ability is not ideal.

III. PROPOSED METHOD

A. GLOBAL-BASED SPF

It is clearly that only depending on the global intensity information is not sufficient when object and background regions of real images are not homogenous. Inspired by the work in [29], [30], we introduce global medians to construct the energy equation. Then, the new global weighted SPF function can be given as follow:

$$\text{spfgw}(I(x)) = \beta(I(x)) \left[ I(x) - \frac{c_1^2 + m^2 - 2c_2^2}{2c_1 + 2m - 4c_2} \right]^2$$ (10)

where $c_1$ and $c_2$ show the average gray value internal and external the regions of $C$, $m$ represent the median intensity of the internal region. There parameters are defined as:

$$\begin{cases}
    c_1 = \text{average}(I(x) \in [x \in \Omega | \phi(x) \geq 0]) \\
    c_2 = \text{average}(I(x) \in [x \in \Omega | \phi(x) < 0]) \\
    m = \text{median}(I(x) \in [x \in \Omega | \phi(x) \geq 0])
\end{cases}$$ (11)

Rather than a constant force, we use an adaptive signs of the pressure force inside and outside the target region to the evolution of the contour curve. It is given as:

$$\beta(I(x)) = \text{sign} \left( I(x) - \frac{c_1^2 + m^2 - 2c_2^2}{2c_1 + 2m - 4c_2} \right)$$ (12)

The proposed global weighted SPF function has the capacity to adjust the signs of the pressure forces and implicit control the propagation of evolutionary curves, which make the contour shrink when they are outside the object of interest and expands when it is inside the object.

B. LOCAL-BASED SPF

In order to make the model can deal images with intensity inhomogeneous, the local weighted SPF function is introduced as the coefficients of local internal and external regions. The local-based SPF function is computed as:

$$\text{spflw}(I(x)) = \frac{I(x) - (d_{lw1}f_1 + d_{lw2}f_2)}{\max(|I(x) - (d_{lw1}f_1 + d_{lw2}f_2)|)}$$ (13)

where $d_{lw1}$ and $d_{lw2}$ are two normalized absolute local intensity differences of pixel intensities of internal and external regions. It is given as:

$$d_{lw1} = \frac{d_{in}}{d_{in} + d_{out}}, \quad d_{lw2} = \frac{d_{out}}{d_{in} + d_{out}}$$ (14)

where $d_{in}$ and $d_{out}$ show the amount of the local intensity differences internal and external the evolving curve in local region, which can be computed by:

$$\begin{cases}
    d_{in} = \text{Num}(I(x) - f_1) \geq 0 \\
    d_{out} = \text{Num}(I(x) - f_1) < 0
\end{cases}$$ (15)

where $f_1$ and $f_2$ represent fitting functions approaching intensity value inner and outer local regions.

$$\begin{cases}
    f_1 = \text{average}(I(y) \in \{x \in \Omega | \phi(x) \geq 0 \} \cap W_k(x)) \\
    f_2 = \text{average}(I(y) \in \{x \in \Omega | \phi(x) < 0 \} \cap W_k(x))
\end{cases}$$ (16)

where $W_k(x)$ is a rectangular window function, e.g. a truncated Gaussian window or a constant window. In our experiment, we select the window size $(4k + 1) \times (4k + 1)$, where $k$ is a positive integer. Unlike the global weighted SPF function, the evolving curve can weight local inner and outer region fitting centers better, and it make segmentation performance more accurate.

C. LEVEL SET FORMULATION

In order to segment weak boundary and inhomogenous image, we build a new SPF function by using the global weighted SPF in (10) and local weighted SPF in (13), which can be expressed as:

$$\text{spfnew}(I(x)) = \text{w}(x) \text{spfgw}(I(x)) + (1 - \text{w}(x)) \text{spflw}(I(x))$$ (17)

where $\text{w}(x)$ is an adaptive weighting function that adjust the local-based SPF and global-based SPF energies. As we can see, in the region close to the edge of the target and where the intensities are changing violently, we should increase the weight of local term. In the region far away from the edge of the target where intensities vary slowly, the weight of the global-based SPF energy should be increased in such areas.

Inspiration by the work in [31], we choose the adaptive weight:

$$\text{w}(x) = \lambda \cdot \text{average}(C_N) \cdot (1 - C_N)$$ (18)
where $\lambda$ is a fixed constant and $C_N$ is a local contrast ratio of a given image defined as:

$$C_N = \frac{M_{\text{max}} - M_{\text{min}}}{M_g}$$  \hspace{1cm} (19)

where $N$ represents the size of the local window, $M_{\text{max}}$ and $M_{\text{min}}$ are the maximum and minimum of the intensities within this local window, respectively. $M_g$ shows the intensity level of whole image. Obviously, $C_N$ ranges from 0 to 1. It shows how quickly the intensity changes in a local quickly. The value of $C_N$, with a larger value representing evolving close to edges and smaller in smooth regions. It should be noted that average($C_N$) is the average value of $C_N$ over the whole image and it shows the overall contrast information of the image. Obviously, the weight functions $w(x)$ and $1 - w(x)$ are also vary between 0 and 1. In homogeneous regions, the global-based SPF is dominant and the weight function $w(x)$ is large. In inhomogeneous areas, the local-based SPF is dominant and the weight function $1 - w(x)$ is large. Therefore, the weight functions $w(x)$ and $1 - w(x)$ can automatically adjust the local term and the global term in all regions.

Substituting the SPF function in (17) for the ESF in (9), the total evolution equation can be expressed as:

$$\frac{\partial \phi}{\partial t} = \text{spf}_{\text{new}}(I(x))\alpha|\nabla \phi|$$  \hspace{1cm} (20)

where $\alpha$ is the balloon force that controls the expansion or contraction of a contour within or outside the object boundaries.

D. IMPLEMENTATION

The procedures of our algorithm can be summarized as:

Step 1: Initialize the level set function $\phi = \phi^0(x)$ to be a binary function:

$$\phi^0(x) = \begin{cases} -c_0 & x \text{ is inside } C \\ 0 & x \in C \\ c_0 & x \text{ is outside } C \end{cases}$$  \hspace{1cm} (21)

Step 2: Compute the global weighted SPF term with (10).

Step 3: Compute the local weighted SPF term with (13).

Step 4: Compute the new SPF function combing the global weighted SPF and the local weighted SPF functions with (17).

Step 5: Obtain the level set according to (20).

Step 6: Regularize the level set function with a Gaussian filter.

Step 7: Check whether contour evolution is converged or the fixed iterative times are reached do. If not, return to step 2.

IV. RESULTS AND ANALYSIS

In this subsection, ACM LoG model [32], ACM LPF model [33], C-V model [17], SBGFRLS model [27], RSF model [18], ORACM model [34], Sun’s model [35] and our model are used on a series of real and synthetic images. Unless otherwise stated, we employ: the Gaussian kernel width $k = 3$, time step $\Delta t = 1$, $\alpha = 15$, $\varepsilon = 1.5$.

A. RESULTS ON SYNTHETIC IMAGES

In order to verify the robustness of our method for contour initialization, experiments are tested on three synthetic
images with five different initial contours, as shown in Figs. 1, 2 and 3. The original image with red initial contours are displayed in the first column in each figure, and the corresponding results of ACM_LoG mode, ACM_LPF model, C-V model, SBGFRLS model, RSF model, ORACM model, Sun’s model and our method are shown in order from the second to last columns, respectively. Fig. 1 is a finger image with two middle fingers stick together, Fig. 2 is a plane image with distinct shadow, Fig. 3 is a multiple object image with five different intensities. From the segmentation result we find that the C-V, SBGFRLS and ORACM used the global statistical information of the images, they cannot address well the segmentation of multi-phase images. The RSF and Sun’s models can effectively obtain desired boundary on all three image when the initial contour is properly placed, but fails to extract from others, because the local statistical information utilized by these models are easily disturbed by the intensity of a certain point. By combining of the global information, ACM_LoG, ACM_LPF and our methods can successfully detect images with multi-phase objects and intensity non-uniformity, even though we choose the different initial contour.

B. RESULTS ON REAL IMAGES

The purpose of the experiment is to verify the superiority of our method to segment images with different noise levels, including Gaussian noise, and salt & pepper noise. In general, the real images consist of the clean images polluted by one or more types of the above noise. Artificial noise...
of various grades is added to these images utilizing Matlab function imnoise. In order to ensure the fairness of the experiment, we utilize the same initial contour for all the models. For quantitative comparisons with different methods, we use Jaccard similarity (JS) [36] to test the images on Figs. 4, 5, 6 and 7, respectively. If $S_1$ and $S_2$ denote the segmentation results enclosed by contours obtained by a given algorithm and the ground truth respectively, then the metric
is defined:

$$JS(S_1, S_2) = \frac{N( S_1 \cap S_2)}{N( S_1 \cup S_2)}$$

where $N(\cdot)$ indicates the number of pixels in the enclosed region. The value of $JS$ ranges from 0 to 1, with a higher value representing a more accurate segmentation result.

Figs. 4 and 5 show the segmentation results achieved by several models with the different level of Gaussian noise. From first to last columns, the noise images with four different initial contours are displayed in the first column, and the results of ACM_LoG mode, ACM_LPF model, C-V model, SBGFRLS model, RSF model, ORACM model, Sun’s model and our method are shown in order from the second to last columns, respectively. Their corresponding $JS$ values are listed in Fig. 8a and 8b. It is easily to see that the SBGFRLS and ORACM can achieve good results with one image and poorly with the other. The ACM_LoG, ACM_LPF and C-V, they have the worst results since its energy function is easy to fall into local minima. For RSF and Sun’s, when the noise of the images is not strong, both of them can get the high $JS$ values. However, the $JS$ values decrease distinctly with increasing noise density. Our model has higher $JS$ values among these methods as it combines of the local information and global information.

In the next experiments, we verify the effectiveness of our model on images with various Salt & pepper noises level, as shown in Figs. 6 and 7. Their corresponding $JS$ values are shown in Fig. 8c and 8d. Similarly, when the noise strength is not strong, all the models can accurately capture the object, and present a decent visual effect. However, if the noise increases distinctly, their results become worse and they
can wrongly classify the background as the object. It also demonstrates that our method can obtain desired results with different levels of speckle noises.

C. RESULTS ON NATURAL IMAGES

In reality, intensity inhomogeneity often exists in the natural images. In this subsection, we selected 6 images for experimentation from Berkeley Image Segmentation Dataset [37]. The natural images have serious intensity inhomogeneity and the background areas which contain the similar intensity with the target areas often disturb the segmentation results. From Fig. 9 we can easily observe that our model successfully extracted the object boundaries on these nature images.

D. COMPARATIVE EVALUATION RESULTS

To evaluate the performance of the proposed method, quantitative and visual experiments have been carried out on two groups of the whole cerebral hemorrhage CT images (the image size is 256 * 256), as shown in Figs. 10 and 11. These images are from Quzhou People Hospital, Quzhou, China. Different from synthetic images and real images, medical images may have much noise and weak edges. The Jaccard similarity (JS) values are computed to quantify the outputs of the proposed method and other state-of-art segmentation methods as compared with the ground truths which were completed by one well-trained radiologist. The columns in Figs. 10 and 11 from left to right are the original image with red initial contours, the results obtained with ACM_LoG, ACM_LPF, C-V, SBGFRLS, RSF, ORACM, Sun’s and our method, respectively. It can be clearly seen that SBGFRLS, ORACM and our method have achieved better segmentation results than the other five models. Fig. 12 lists the evaluation results of these models by using JS values in Figs. 10 and 11. It can be seen from Fig. 12 that the JS values of our method is
FIGURE 11. Results for cerebral hemorrhage CT images. From first to last columns: the images with red initial contour, ACM_LoG, ACM_LPF, C-V, SBGFRLS, RSF, ORACM, Sun’s and our method. Parameter settings of our model: the Gaussian kernel width $k = 5$, $\alpha = 18$.

FIGURE 12. JS values for images in Figs. 10 and 11, respectively.

|       | ACM_LoG | ACM_LPF | C-V   | SBGFRLS | RSF   | ORACM  | Sun’s  | our method |
|-------|---------|---------|-------|---------|-------|--------|--------|------------|
| Iterations/Time |         |         |       |         |       |        |        |            |
| Fig. 10 | 1   | 130 | 16.002 | 150 | 22.233 | 30 | 3.141 | 50 | 1.451 | 120 | 6.938 | 40 | 1.924 | 50 | 9.219 | 20 | 4.157 |
| 2   | 120 | 14.728 | 150 | 21.919 | 30 | 4.071 | 50 | 1.416 | 400 | 39.537 | 30 | 1.287 | 850 | 125.349 | 20 | 3.765 |
| 3   | 780 | 83.297 | 250 | 28.405 | 30 | 4.149 | 50 | 1.477 | 240 | 49.385 | 30 | 1.289 | 250 | 39.299 | 80 | 9.892 |
| 4   | 800 | 83.675 | 150 | 23.458 | 30 | 4.289 | 50 | 1.457 | 180 | 17.988 | 30 | 1.301 | 200 | 30.653 | 80 | 9.790 |
| 5   | 1200 | 123.490 | 150 | 21.608 | 30 | 4.342 | 50 | 1.419 | 120 | 12.194 | 30 | 1.291 | 150 | 23.398 | 60 | 7.979 |
| 6   | 150 | 18.826 | 150 | 22.606 | 30 | 4.108 | 50 | 1.567 | 140 | 14.095 | 40 | 1.604 | 100 | 16.090 | 60 | 6.428 |
| 7   | 150 | 19.670 | 200 | 24.527 | 30 | 4.784 | 50 | 1.487 | 200 | 19.969 | 60 | 3.240 | 300 | 30.419 | 40 | 4.324 |
| 1   | 300 | 34.665 | 150 | 22.565 | 30 | 3.267 | 50 | 1.505 | 100 | 9.702 | 40 | 2.210 | 50 | 9.129 | 40 | 5.827 |
| 2   | 300 | 35.618 | 150 | 22.726 | 30 | 3.105 | 50 | 1.542 | 160 | 15.465 | 60 | 4.069 | 50 | 9.569 | 40 | 5.833 |
| 3   | 400 | 49.007 | 150 | 22.542 | 30 | 3.105 | 50 | 1.391 | 400 | 38.354 | 70 | 4.671 | 200 | 30.740 | 40 | 5.759 |
| 4   | 200 | 26.496 | 100 | 18.690 | 30 | 3.139 | 50 | 1.434 | 400 | 39.321 | 70 | 4.734 | 100 | 16.301 | 40 | 5.794 |
| 5   | 200 | 25.888 | 100 | 18.595 | 30 | 3.160 | 50 | 1.537 | 180 | 17.884 | 80 | 4.663 | 250 | 37.186 | 40 | 5.908 |
| 6   | 110 | 18.999 | 100 | 18.393 | 30 | 3.137 | 200 | 7.756 | 200 | 20.366 | 70 | 3.554 | 100 | 15.516 | 80 | 9.698 |

TABLE 1. Iteration and computation time of the images in Figs. 10 and 11.

E. COMPUTATIONAL TIME

To verify the computational times of the proposed method, the model on the images in Figs. 10 and 11 are tested.
The whole system was implemented on PC with Core i7-7700HQ CPU running at 281 GHz with 8 GB of memory and 64 bit operating system loaded with Matlab R2014a. The results regarding the iteration numbers and the CPU times (in seconds) are illustrated in Table 1. It can be seen that the C-V, SBGFRLS and ORACM take the shortest time as compared to the other five methods. However, they cannot handle strong noise and high intensity inhomogeneity well. The runtime in our method is higher than these models since our model needs to compute the local and global fitting terms. However, it is worthwhile to segment images influenced by different noise and intensity inhomogeneity when we need accurate segmentation results.

V. CONCLUSION

This study presented a novel hybrid active contour method which combines the local and global statistical information into an improved signed pressure force (SPF) function. The two most important innovation of our model is to define a new global-based SPF function which can efficiently adjusts the signs of the pressure force inside and outside the contour and a new local-based SPF function utilizes the normalized local intensity differences as the coefficients of local internal and external regions. Then, a weight function is established to adjust the effect degrees between the above two SPF functions. Experimental results demonstrate that our model makes superior segmentation accuracy and is more robust to initial contour and noises.

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