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GPU Accelerated Level Set Non-Homogenous Image Segmentation Solving by Lattice Boltzmann Method

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Abstract: A novel hybrid fitting energy based active contours model in the level set framework is proposed. The method fuses the local image fitting term and the global image fitting term to drive the contour evolution. Our model can efficiently segment the images with intensity inhomogeneity no matter where the initial curve is located in the image. In its numerical implementation, an efficient numerical scheme called Lattice Boltzmann Model (LBM) is used to break the restrictions on time step, compared with the traditional schemes, the LBM strategy can further shorten the time consumption of the evolution process, this allows the level set to quickly reach the true target location. In addition, the proposed LSM is implemented using an NVIDIA graphics processing units (GPU) to fully take advantage of the LBM local nature. The extensive and promising experimental results on synthetic and real images demonstrate subjectively and objectively the performance of the proposed method.

1. Introduction

Image segmentation is a fundamental task in many image processing and computer vision applications. Due to the presence of noise, low contrast, and intensity inhomogeneity, it is still a difficult problem in majority of applications.

Image segmentation in general has been studied extensively in the past decades. A well-established class of methods are active contour models [1], [2], [3], which are based on the theory of surface evolution and geometric flows, have been extensively studied and successfully used in image processing. The level set method (LSM) proposed by Osher and Sethian [4]is widely used in solving the problems of surface evolution. Later, geometric flows were unified into the classic energy minimization formulations for image segmentation [5], [6], [7], [8]. Generally speaking, the existing active contour models can be categorized into two types: edge-based models [9], [10] and region-based models [11], [12]. Each of them has its own pros and cons.

The edge-based models, which usually utilize the gradient information of the image to construct an edge detector to push the contours toward the desired boundaries of the objects and finally ensure that the evolution curve converges to these boundaries. In order to expand the capture scope of the driving force, a balloon force term is often included in the evolution function, which is used to control the contour to shrink or expand. In the practice of image segmentation with strong edges, they have achieved a lot of successful applications. However, they may suffer from some terrible problems such as level set initialization, edge leakage, and falling into local minimum value, for image segmentation applications, the existence of these problems will lead to the segmentation model is difficult to output desired analytical results.

Region-based active contour models use the regional statistical information from inside and outside of the evolution contour to construct the constraining force to guide the whole level set evolution process. Compared with the edge-based models, region-based models have the following obvious advantages: First, region-based models have more freedom in terms of the contour initialization, i.e., the initial contour can be located anywhere in the image coordinate system, and the exterior and interior contours can be detected simultaneously. Second, they are very insensitive to noise and can efficiently segment the images with weak edges or even without edges. One of the most successful region-based models is the C-V model, which has been widely used in binary phase segmentation with the assumption that each image region is statistically homogeneous. However, the C–V model fails to segment the images with intensity inhomogeneity.

In order to overcome the segmentation difficulty caused by the intensity inhomogeneity, Zhang et al. [13] proposed a local image fitting (LIF) model, it utilizes the local region information and thus can provide accurate segmentation results. However, the final convergence result of the LIF model is related to the initial position of the curve, this means that LIF model is sensitive to the initial position of the curve, which greatly limits the scope of its practical application.

In this paper, we propose a new region-based active contour model which can get better segmentation results when the intensity of the image is not uniform. In order to improve the performance of the LIF model in terms of the degree of freedom of the initial curve position, we add a global image fitting term to the energy functional of the LIF model.

After the construction of the active contour model, we need to choose the appropriate numerical solution to solve our model. In order to solve the active contour model in the level set framework, most classical methods such as the upwind scheme are based on some finite difference, finite volume or finite element approximations and an explicit computation of the curvature [14]. Since only a very small time step can be taken, thus all of these methods require a large amount of CPU time to complete their evolution process.

Recently, the lattice Boltzmann method (LBM) has been introduced as an alternative scheme for solving level set equation [15]. It can better handle the high computation problem because the curvature is implicitly computed and the complexity of the algorithm is very low and has a characteristic of high degree of parallelism, in addition, due to the use of very large time step, the evolution process will be greatly accelerated. In view of the aforementioned advantages, we use LBM to solve our level set equation.

Over the past few years, the GPU has been proposed as a general-purpose computing architecture. As the simple increase in the clock speed will push the transistors to thermal limits, the multi-core technology has become an obvious solution to enhance the computing performance. In this context, The GPU has been recognized as one of the most promising techniques to accelerate scientific computations. The GPU architecture favors dense data and local computations because the communications between microprocessor is time consuming. Since the majority of LBM with local characteristics, therefore, it is particularly suitable for GPU-based computation. For this reason, we adopt the NVIDIA graphics processing units to speed up the proposed level set segmentation algorithm.

The remainder of this paper is organized as follows. Section 2 is a brief description of the classical C-V and LIF models. Section 3 presents the formulation and implementation of the proposed model. Section 4 validates the proposed model by extensive experiments on synthetic and real images. Last, conclusions are drawn in section 5.

2. The review and discussion of related works

2.1. C-V model

In the classical active contour model, the external energy is mainly dependent on the local edge gradient information to detect the potential objects in an image. However, for images whose boundaries are either smooth or not necessarily defined by gradient, it will be difficult to obtain desired results. In order to solve this problem effectively, Chan and Vese [11] proposed a new active contour model which was based on the simplified Mumford-Shah model, commonly referred to as C-V model. The model depends on the global information of homogeneous regions, the energy functional is defined as follows:

$$E\left(C, M_{in}, M_{out}\right)=\lambda_1 \int_{in(C)}\left(I-M_{in}\right)^2 dxdy+\lambda_2 \int_{out(C)}\left(I-M_{out}\right)^2 dxdy+\mu \cdot L\left(C\right)+\nu \cdot S\left(in\left(C\right)\right) \tag{1}$$

where μ, ν, λ_1 and λ_2 are positive constants, we generally choose the parameters as follows:

$\lambda_1 = \lambda_2 = 1, \nu = 0$. M_{in} and M_{out} are the intensity averages of $I(x,y)$ inside C and outside C, respectively.

In order to solve this minimization problem, the level set method is introduced which represents the curve C by the zero level set of a Lipschitz function $\phi(x,y):\Omega \to R$, such that $\phi(x,y) > 0$ if the point (x,y) is inside C, $\phi(x,y) < 0$ if (x,y) is outside C, and $\phi(x,y) = 0$ if (x,y) is on C. Thus the energy functional $Energy(C, M_{in}, M_{out})$ can be reformulated in terms of the level set function $\phi(x,y)$ as follows:

$$\begin{aligned} E_\varepsilon(C, M_{in}, M_{out}) &= \lambda_1 \int_\Omega (I - M_{in})^2 H_\varepsilon(\phi)\, dxdy + \\ &\lambda_2 \int_\Omega (I - M_{out})^2 (1 - H_\varepsilon(\phi))\, dxdy + \mu \cdot \int_\Omega \delta_\varepsilon(\phi)|\nabla\phi|\, dxdy + \nu \cdot \int_\Omega H_\varepsilon(\phi) dxdy \end{aligned} \tag{2}$$

This minimization problem is solved by deducing the associated Euler-Lagrange equations and updating the level set function $\phi(x,y)$ by the gradient descent method (with $\phi(0,x,y) = \phi_0(x,y)$ defining the initial contour):

$$\frac{\partial\phi}{\partial t} = \delta_\varepsilon(\phi)\left[\mu div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - \nu - \lambda_1 (I - M_{in})^2 + \lambda_2 (I - M_{out})^2\right] \tag{3}$$

where M_{in} and M_{out} can be updated iteratively by

$$M_{in}(\phi) = \frac{\int_\Omega I \cdot H_\varepsilon(\phi) dxdy}{\int_\Omega H(\phi_\varepsilon) dxdy}, M_{out}(\phi) = \frac{\int_\Omega I \cdot (1 - H_\varepsilon(\phi)) dxdy}{\int_\Omega (1 - H(\phi_\varepsilon)) dxdy} \tag{4}$$

and $-\lambda_1 (I - M_{in})^2 + \lambda_2 (I - M_{out})^2$ is the global image fitting force, which uses the global image information of the input image to guide the evolution of level set model. As a representative region information-based level set segmentation model, the C-V model has an important characteristic, that is, its evolution is not sensitive to the initial position of the curve. However, when the intensity of the image is not homogeneous, the difference between the two means (M_{in} and M_{out}) and the real image data will be very large, this phenomenon will inevitably lead the C-V model to be difficult to give an ideal segmentation result.

2.2. LIF model

Kaihua Zhang et al. [13] proposed a novel region-based active contour model which taking full account of the local information of the image and some good segmentation results are obtained on the non-homogeneous images. The energy functional is defined as follows:

$$E^{LIF}(\phi, u_1, u_2) = \frac{1}{2}\int_\Omega \left|I(x) - I^{LFI}(x)\right|^2 dx \tag{5}$$

where I^{LFI} is the local fitted image which can be defined as follows:

$$I^{LFI} = u_1 H_\varepsilon(\phi) + u_2 (1 - H_\varepsilon(\phi)) \tag{6}$$

where u_1 and u_2 are defined as:

$$u_1 = average\left(I \in \left(\{x \in \Omega | \phi(x) < 0\} \cap W_k(x)\right)\right), u_2 = average\left(I \in \left(\{x \in \Omega | \phi(x) > 0\} \cap W_k(x)\right)\right) \tag{7}$$

where $W_k(x)$ is a rectangular window function such as a truncated Gaussian window or a constant window. Minimizing the energy functional with respect to ϕ by using the calculus of variation and the steepest descent method, we can easily deduce the corresponding gradient descent flow as:

$$\frac{\partial\phi}{\partial t} = (I - I^{LFI})(u_1 - u_2)\delta_\varepsilon(\phi) \tag{8}$$

In the above equations (Including the C-V model of section 2.1.), we actually use the regularized versions of Heaviside function H and Dirac function δ which are expressed as follows:

$$H_{\varepsilon}(z)=\frac{1}{2}\left[1+\frac{2}{\pi}\arctan\left(\frac{z}{\varepsilon}\right)\right],\delta_{\varepsilon}(z)=\frac{1}{\pi}\cdot\frac{\varepsilon}{\varepsilon^{2}+z^{2}},\quad z\in R \tag{9}$$

The parameter ε affects the profile of $\delta_{\varepsilon}(\phi)$. A bigger ε will cause a broader profile, which will expand the capture scope but decrease the accuracy of the final contour.

In actual calculation, the construction process of the local fitted image $\left(I-I^{LIF}\right)\left(u_1-u_2\right)$ is based on all the pixels in a local rectangle window, this localization property is the real reason for the LIF model to be able to segment non-homogenous images. However, when the contour is located at a certain location where $u_1=u_2$, the local image fitting force will be zero, which leads to the evolution process be trapped into certain local minima, thus the segmentation result has a strong correlation with the initial position of the curve.

3. The proposed model

3.1. The formulation of the proposed model

After being inspired by the two models of C-V and LIF, we define the energy functional as follows:

$$\begin{aligned}&E^{local-global}\left(\phi,M_{in},M_{out},u_1,u_2,\sigma_1^2,\sigma_2^2\right)=(1-\beta)E^{LIF}+\\&\beta\left(\lambda_1\int_{\Omega}\left(I-M_{in}\right)^2H_{\varepsilon}(\phi)dxdy+\lambda_2\int_{\Omega}\left(I-M_{out}\right)^2\left(1-H_{\varepsilon}(\phi)\right)dxdy\right)\end{aligned} \tag{10}$$

where β is a weight control parameter and its value is located within the interval $[0,1]$.

For more accurate computation involving the level set function and its evolution, we need to regularize the level set function by penalizing its deviation from a signed distance function [17], characterized by the following energy functional: $P(\phi)=\int\frac{1}{2}\left(\left|\nabla\phi(x)\right|-1\right)^2dx$.

As in typical level set methods, we need to regularize the zero level set by penalizing its length to derive a smooth contour which is as short as possible during evolution: $L(\phi)=\int\left|\nabla H\left(\phi(x)\right)\right|dx$.

In summary, we can express the total energy functional as the following:

$$E_{total}=a\cdot E^{local-global}+b\cdot P(\phi)+c\cdot L(\phi) \tag{11}$$

where a, b and c are control parameters to balance the contribution of each energy term.

Keeping M_{in} and M_{out} fixed, and minimizing the entire energy functional Energy with respect to ϕ, we deduce the associated Euler–Lagrange equation for ϕ as follows:

$$\begin{aligned}\frac{\partial\phi}{\partial t}&=\beta\delta_{\varepsilon}(\phi)\left(-\lambda_1\left(I-M_{in}\right)^2+\lambda_2\left(I-M_{out}\right)^2\right)-(1-\beta)\delta_{\varepsilon}(\phi)\left(I-I^{LIF}\right)\left(u_1-u_2\right)\\&+\eta\left(\Delta\phi-div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right)+\mu\delta_{\varepsilon}(\phi)div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\end{aligned} \tag{12}$$

where M_{in}, M_{out}, u_1 and u_2 are formulated by expressions (4), and (7), respectively.

The new hybrid fitting energy is a weighted linear combination of the global image fitting force from the C-V model and the local image fitting force from the LIF model. The advantages of this weighted combined form of image fitting energy are as follows: The global image fitting force component makes the combined model insensitive to the initial position of the curve, and the local image fitting force component makes the combined model can segment the images with intensity inhomogeneity. We combine these two forces together with the control parameter β so that the new hybrid model can have the advantages of the C-V model and the LIF model. Therefore, the proposed model can effectively deal with the intensity inhomogeneity, regardless of the initial contour starting at the image.

The parameter β plays an important role to balance the contribution of the aforementioned two forces, which should be determined based on the degree of inhomogeneity of the current image. When there is serious inhomogeneity in the image, we need to select a small parameter β, in this case, the driving force of contour evolution is mainly from the local image fitting force. On the contrary, if the inhomogeneity effect is not obvious, we have to select a bigger parameter β in which case the evolution process of the curve is mainly controlled by the global image fitting force.

The proposed hybrid level set model is constructed based on the core processing ideas of the C-V model and LIF model. If we set the parameter β in formula (10) to 1 and 0, our model will be degraded to the C-V model and LIF model, respectively. However, our model takes into account both the local and global image information, therefore, its segmentation performance is better than the C-V model and LIF model in general.

3.2. The implementation of the proposed model

3.2.1. The reason for the high computational complexity of traditional level set methods

The traditional level set methods usually need to spend more iterative times (corresponding to a higher time consumption) to segment an image, which is unacceptable for image data-based real time applications or mass image data processing problems. The following reason leads to this high computational complexity phenomenon: An explicit scheme is the most popular way for solving Eq. (12), but due to the Courant-Friedreichs-Lewy (CFL) [18] condition which asserts that the numerical waves should propagate at least as fast as the physical waves, so the curve can only move a small distance in each iteration, it requires very small time step and if the curve is not near the edge of interested object, the curve may take a long time to reach the final position.

3.2.2. Lattice Boltzmann Method for breaking the restrictions on time step

The CFL condition limits the time step of the traditional numerical solution of the level set equation, which leads to the increase of the number of iterations in the evolution process. Under the finite difference framework, the process needs to approximate the continuous PDE to a discrete form, while LBM [19] derives a continuous PDE which has the same form of the level set equation from a discrete form. Since the time step is not strongly restricted and highly parallelizable, LBM is a fast numerical solution of the level set equation.

LBM is proposed as a computational fluid dynamics (CFD) method for fluid modeling [20]. Instead of solving the Navier-Stokes equations, the discrete boltzmann equation is solved to simulate the flow of the Newtonian fluid by collision models such as Bhatnagar-Gross-Krook (BGK) [21], [22].

In this paper, we use the D2Q9 (2D with 8 links with its neighbors and one link for the cell itself) LBM lattice structure. Fig. 1 shows a typical D2Q9 model.

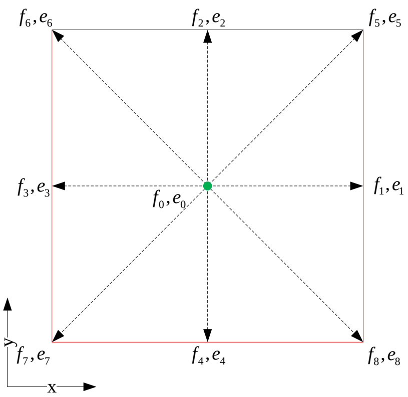

Fig. 1 Spatial structure of the D2Q9 LBM lattice

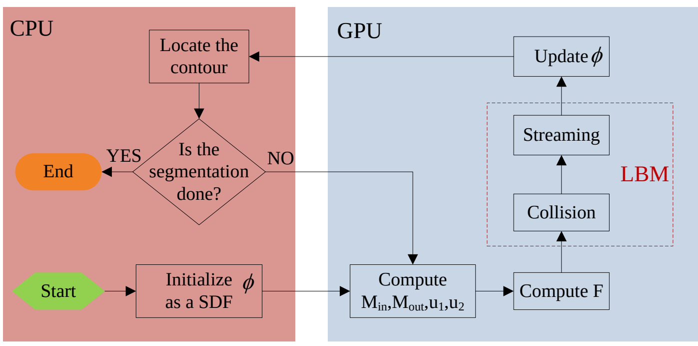

Fig. 2 The flowchart the proposed GPU accelerated segmentation model

The evolution equation of LBM can be written as

$$f_i\left(\vec{r}+\vec{e_i}\Delta t, t+\Delta t\right)=f_i\left(\vec{r},t\right)+\frac{1}{\tau}\left[f_i^{eq}\left(\vec{r},t\right)-f_i\left(\vec{r},t\right)\right]+\frac{D}{bc^2}\cdot\vec{F}\cdot\vec{e_i} \quad (13)$$

where $\vec{e_i}$ is the velocity vector of a given link i, $f_i\left(\vec{r},t\right)$ the distribution of the particle that moves along that link, t the time, Δt the time step, $\vec{r}$ the position of the cell, $\vec{F}$ the body force, D the grid dimension, b the link at each grid point and c the length of each link which is set to 1 in this paper. The parameter τ represents the relaxation time determining the kinematic viscosity in Navier-Stokes equations, and f_i^{eq} is the local equilibrium particle distribution which has the following form.

$$f_i^{eq}\left(\rho,\vec{u}\right)=\rho\left(A_i+B_i\left(\vec{e_i}\cdot\vec{u}\right)+C_i\left(\vec{e_i}\cdot\vec{u}\right)+D_i\left(\vec{u}\right)^2\right) \quad (14)$$

where the constant coefficients A_i to D_i are determined based on the geometry of the lattice links, ρ and $\vec{u}$ are respectively the macroscopic fluid density and velocity calculated from the particle distributions as

$$\rho=\sum_i f_i, \vec{u}=\frac{1}{\rho}\sum_i f_i\vec{e_i} \quad (15)$$

For diffusion problems, the equilibrium function can be simplified as [15]

$$f_i^{eq}\left(\rho,\vec{u}\right)=\rho A_i \quad (16)$$

In the case of D2Q9 structure, the concrete form of f_i^{eq} is

$$f_i^{eq}=\rho\alpha_i\left(1+3\left(\vec{e_i}\cdot\vec{u}\right)+\frac{9}{2}\left(\vec{e_i}\cdot\vec{u}\right)^2-\frac{3}{2}\left(\vec{u}\right)^2\right),\quad i=0,1,\cdots,8 \quad (17)$$

where $\alpha_0=4/9, \alpha_{1,2,3,4}=1/9, \alpha_{5,6,7,8}=1/36$, at the same time, there is a relationship between the relaxation time τ and the diffusion coefficient γ:

$$\gamma=\frac{2}{9}\left(2\tau-1\right) \quad (18)$$

By performing the Chapman-Enskog analysis the following diffusion equation can be recovered from the LBM evolution equation [15]:

$$\frac{\partial\rho}{\partial t}=\gamma\ \nabla\cdot\nabla\rho+F \quad (19)$$

By replacing ρ with the signed distance function ϕ in Eq. (21), since level set function ϕ has the signed distance property $\left|\nabla\phi\right|=1$, we have the following expression:

$$\frac{\partial\rho}{\partial t}=\gamma\ \nabla\cdot\nabla\rho+F=\gamma div\left(\frac{\nabla\phi}{\left|\nabla\phi\right|}\right)+F \quad (20)$$

where “div” is the divergence operator, and the body force F represents the link with the image data in the LBM solver. Table 1 gives the corresponding forms of τ and F in D2Q9 LBM equation for the C-V model, LIF model and our model described in subsection 3.1., the proposed level set equation can therefore be solved using the following lattice Boltzmann equation:

$$\begin{aligned}&f_i\left(\vec{r}+\vec{e_i}\Delta t, t+\Delta t\right)=f_i\left(\vec{r},t\right)+\frac{1}{\tau}\left[f_i^{eq}\left(\vec{r},t\right)-f_i\left(\vec{r},t\right)\right]+\\&\frac{D}{bc^2}\cdot\left(a\cdot\beta\cdot\delta_\varepsilon\left(\phi\right)\left(-\lambda_1\left(I-M_{in}\right)^2+\lambda_2\left(I-M_{out}\right)^2\right)-a\cdot\left(1-\beta\right)\cdot\delta_\varepsilon\left(\phi\right)\left(I-I^{LIF}\right)\left(u_1-u_2\right)+b\cdot\Delta\phi\right)\end{aligned} \quad (21)$$

After adopting the LBM ideology, we do not need to explicitly calculate the curvature since it is implicitly handled by the LBM.

Table 1 Corresponding forms of τ and f in D2Q9 LBM equation for level set methods

Method	Level set equation	τ and F
C-V model	$\frac{\partial\phi}{\partial t}=\delta_\varepsilon(\phi)\left[\mu div\left(\nabla\phi/\|\nabla\phi\|\right)-\nu-\lambda_1\left(I-M_{in}\right)^2+\lambda_2\left(I-M_{out}\right)^2\right]$	$\tau=\frac{9}{4}\cdot\mu\cdot\delta_\varepsilon(\phi)+0.5$, $F=\delta_\varepsilon(\phi)\left[-\nu-\lambda_1\left(I-M_{in}\right)^2+\lambda_2\left(I-M_{out}\right)^2\right]$
LIF model	$\frac{\partial\phi}{\partial t}=-\delta_\varepsilon(\phi)\left(I-I^{LIF}\right)\left(u_1-u_2\right)$	/
Our model	$\frac{\partial\phi}{\partial t}=a\cdot\beta\cdot\delta_\varepsilon(\phi)\left(-\lambda_1\left(I-M_{in}\right)^2+\lambda_2\left(I-M_{out}\right)^2\right)-a\cdot(1-\beta)\cdot\delta_\varepsilon(\phi)\left(I-I^{LIF}\right)\left(u_1-u_2\right)+b\cdot\left(\Delta\phi-div\left(\frac{\nabla\phi}{\|\nabla\phi\|}\right)\right)+c\cdot\delta_\varepsilon(\phi)div\left(\frac{\nabla\phi}{\|\nabla\phi\|}\right)$	$\tau=\frac{9}{4}\cdot\left(c\cdot\delta_\varepsilon(\phi)-b\right)+0.5$, $F=a\cdot\beta\cdot\delta_\varepsilon(\phi)\left(-\lambda_1\left(I-M_{in}\right)^2+\lambda_2\left(I-M_{out}\right)^2\right)-a\cdot(1-\beta)\cdot\delta_\varepsilon(\phi)\left(I-I^{LIF}\right)\left(u_1-u_2\right)+b\cdot\Delta\phi$

3.2.3. Algorithm of the GPU accelerated level set model for image segmentation

The aforementioned strategy can effectively overcome the problem of high computational complexity in traditional level set methods. Our GPU accelerated level set algorithm for non-homogenous image segmentation is implemented as follows:

(1) Initialize the level set function ϕ as a signed distance function;

(2) Update M_{in}, M_{out}, u_1 and u_2 using (4) and (7) respectively;

(3) Compute the input of our LBM such as τ and F according to Table 1 and our level set equation (14);

(4) Resolve the level set equation using LBM with (23);

(5) Accumulate the values of $f_i\left(\vec{r},t\right)$ at each grid point with Eq. (18), which updates the values of ϕ and locate corresponding contour;

(6) Return step (2) until the evolution process reaches the state of convergence.

Fig. 2 shows the flowchart the proposed GPU accelerated level set model.

In the concrete realization stage, the built-in Matlab function called *arrayfun* is used to implement the GPU-based accelerated computation process. For example, when calculating the body force F, we take the following function call:

$$\begin{cases}(1)\, image_{GPU}=gpuArray(image);\\(2)\,\text{ModelParameterStructure}_{GPU}=gpuArray(\text{ModelParameterStructure});\\(3)\,F_{GPU}=arrayfun(@bordy\_force, image_{GPU}, \text{ModelParameterStructure});\\(4)\,F=gather(F_{GPU}).\end{cases}$$

The first and the second lines are used to convert the input image and the associated model parameters from the CPU to the GPU, the third line computes the body force on the GPU using the kernel function $body\_force.m$ programmed by Table 1, the last line transfers the computed body force from the GPU to the CPU.

4. Experimental results

In this section, we evaluate the efficiency of our fast hybrid level set algorithm for non-homogenous image segmentation. The experiments are implemented using the parallel computing toolbox of Matlab R2012a installed on a computer with 2.3G Intel Core i7 CPU, 8G RAM and possessing NVIDIA GPU GeForce GT 720M.

4.1. Comparisons with the C-V model

Fig. 3 shows the comparisons of segmentation result between our model and the C-V model on three laser distance images (the relevant simulation principles please refer to literature [23]). For fairness, we set the same initial curves for the two models. From these images, we can find that the non-homogeneity is very obvious. As we expected (the description details are located in section 2.1.), the final convergence of C-V model is very unsatisfactory, however, our model yields accurate segmentation results, all of this is due to the fact that our model combines local and global image energy effectively.

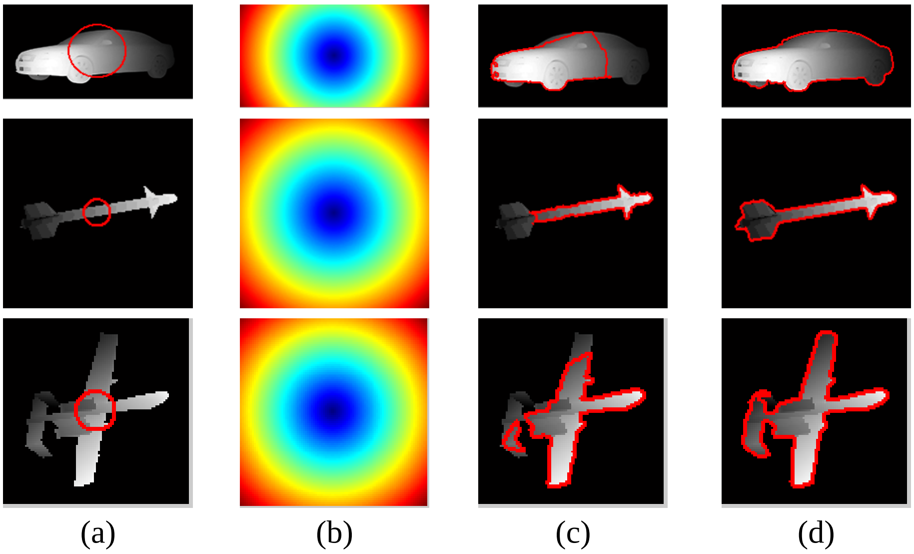

Fig. 3 Comparisons of our model with the C-V model in segmenting four images. Column (a): Initial contour and input image. Column (b): The level set function corresponding to the initial curve. Column (c): Final contour of the C-V model. Column (d): Final contour of our model.

4.2. Comparisons with the LIF model

In order to verify the initial contour position-insensitive characteristic (please refer to section 3.1. for the details of the description) of the proposed model, i.e., the final segmentation result has nothing to do with the starting position of the initial contour, we use our model to segment an infrared image with intensity inhomogeneity shown in Fig. 4.

Fig. 4 (a) shows the initial contours consists of circular clusters of different intervals. Fig. 4 (b) and Fig. 4 (c) show the final locations of the evolution curve by the LIF model and our model, respectively. From the final segmentation results we found that the LIF model outputs are wrong under all three initial conditions, however, our model yields the same exact segmentation results under all initialization forms. This fully shows that the segmentation results of the proposed model have nothing to do with the characteristics of the initial curve.

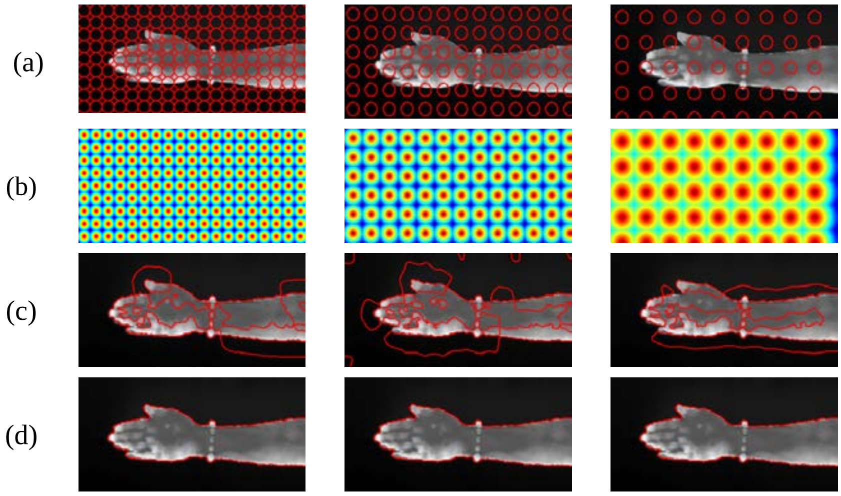

Fig. 4 Comparisons of our model with the LIF model in segmenting an infrared hand image under three different initialization fashions. Row (a): Initial contour and input image. Row (b): The level set function corresponding to the initial curve. Row (c) Final contour of the LIF model. Row (d): Final contour of our model.

4.3. Fast evolution characteristics

In this section, we evaluate the acceleration performance of the two strategies (LBM and GPU) used in this paper. The test images used here are the same as the images shown in Fig. 3 to Fig. 5. In order to make our comparative behavior fair, we only compare the time consumption of iterative process of the algorithms which have similar accurate segmentation results, the methods involved include: method only with the local and global driving characteristic (LGD), method with the local and global driving characteristic and LBM strategy under CPU environment (LGD+LBM+CPU), method with the local and global driving characteristic and LBM strategy under GPU environment (LGD+LBM+GPU). Table 1 shows the comparison results of time cost between the above methods, the sizes of the tested images are also listed. For the images shown in table 2, we take the mean value of the segmentation results.

Table 2 Comparisons between different methods in terms of time cost

Input image	Algorithm	Iterations	Time cost (s)	Accelerated rate
The first row of column (a) of Fig. 3 (200×108 pixels)	LGD	130	22.568	1.0
	LGD+LBM+CPU	61	9.770	2.31
	LGD+LBM+GPU	61	0.195	115.9
The second row of column (a) of Fig. 3 (146×146 pixels)	LGD	50	2.951	1.0
	LGD+LBM+CPU	21	1.341	2.2
	LGD+LBM+GPU	21	0.025	116.6
The third row of column (a) of Fig. 3 (95×95 pixels)	LGD	130	6.222	1.0
	LGD+LBM+CPU	60	2.489	2.5
	LGD+LBM+GPU	60	0.056	111.1
The first row of Fig. 4 (378×180 pixels)	LGD	16	3.753	1.0
	LGD+LBM+CPU	8	1.564	2.4
	LGD+LBM+GPU	8	0.032	118.7

According to the above comparison results, we can deduce the following conclusions: Firstly, the LBM can decrease the number of iterations of the evolution process and reduce the total time cost by several times. Secondly, the acceleration rate of the GPU strategy is even more than one hundred times, therefore, the engineering application value of this strategy is very obvious.

5. Conclusions

This paper presents a GPU accelerated level set algorithm for non-homogenous image segmentation. Our model combines the local and global image energies organically, and use the force formed by these two energies to promote the evolution of the curve. The use of LBM to solve the level set equation enables the algorithm to be highly parallelizable and fast when implemented using an NVIDIA graphics processing units architecture. A large number of experimental results show that our model can quickly and accurately segment the image with non-homogeneous properties, and the final segmentation results are independent of the position of the initial curve. The Experimental results on a variety kind of images have demonstrated subjectively and objectively the effectiveness of the proposed model.

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References

[1] M. Kass, A. Witkin, D. Terzopoulos. Snakes: active contour models, International Journal of Computer Vision, 1988, 1(4): 321-331.

[2] V. Caselles, R. Kimmel, G. Sapiro. Geodesic active contours. in Proceedings of Fifth International Conference on Computer Vision, 1995, 694-699.

[3] G.P. Zhu, Sh.Q. Zhang, Q.SH. Zeng, Ch.H. Wang. Boundary-based image segmentation using

binary level set method. Optical Engineering, 2007, 46(5): 050501-1～050501-3.
[4] S. Osher, J.A. Sethian. Fronts propagating with curvature dependent speed: algorithms based on Hamilton–Jacobi formulations. Journal of Computational Physics, 1988, 79(1): 12-49.
[5] C. Li, C. Kao, J. Gore, Z. Ding. Minimization of region-scalable fitting energy for image segmentation. IEEE Transactions on Image Processing, 2008, 17(10): 1940-1949.
[6] A. Tsai, A. Yezzi, A.S. Willsky. Curve evolution implementation of the Mumford-Shah functional for image segmentation, denoising, interpolation, and magnification. IEEE Transaction on Image Processing, 2001, 10(8): 1169-1186.
[7] L.A. Vese, T.F. Chan. A multiphase level set framework for image segmentation using the Mumford-Shah model. International Journal of Computer Vision, 2002, 50(3): 271-293.
[8] A. Vasilevskiy, K. Siddiqi. Flux-maximizing geometric flows. IEEE Transaction on Pattern Analysis and Machine Intelligence, 2002, 24(12): 1565-1578.
[9] Vicent Caselles, Ron Kimmel and Guillermo Sapiro. Geodesic Active Contours. International Journal of Computer Vision, 1997, 22(1), 61-79.
[10] Chenyang Xu, and Jerry L. Prince. Snakes, Shapes, and Gradient Vector Flow. IEEE Transactions on Image Processing, 1998, 7(3): 359-369.
[11] Tony F. Chan and Luminita A. Vese . Active Contours Without Edges. IEEE Transactions on Image Processing, 2001, 10(2): 266-277.
[12] Remi Ronfard. Region-Based Strategies for Active Contour Models. International Journal of Computer Vision, 1994, 13(2): 229-251.
[13] Kaihua Zhang, HuihuiSong, LeiZhang. Active contours driven by local image fitting energy. Pattern Recognition, 2010, 43: 1199-1206.
[14] S. Osher and R. Fedkiw. Level Set Methods and Dynamic Implicit Surfaces. New York: Springer-Verlag, 2003.
[15] Y. Zhao. Lattice Boltzmann based PDE solver on the GPU. Visual Comput., 2007, 24(5): 323-333.
[16] R. T. Whitaker. A level-set approach to 3D reconstruction from range data. Int. J. Comput. Vis., 1998, 29(3): 203-231.
[17] Chunming Li, Chenyang Xu, Changfeng Gui, and Martin D. Fox. Level Set Evolution Without Re-initialization: A New Variational Formulation. in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, 2005: 430-436.
[18] A. P. Zijdenbos, B. M. Dawant, R. A. Margolin and A. C. Palmer. Morphometric Analysis of White Matter Lesions in MR Images: Method and Validation. IEEE Transactions on Medical Imaging, 1994, 13(4): 716-724.
[19] Q. Chang and T. Yang. A lattice Boltzmann method for image denoising. IEEE Trans. Image Process., 2009, 18(12): 2797-2802.
[20] Y. H. Qian, D. D'Humieres, and P. Lallemand. Lattice BGK models for Navier-Stokes equation. Europhys. Lett., 1992, 17(6): 479-484.
[21] S. Chen and G. D. Doolen. Lattice Boltzmann method for fluid flows. Annu. Rev. Fluid Mech., 1998, 30(1): 329-364.
[22] X. He, Q. Zou, L.-S. Luo, and M. Dembo. Analytic solutions of simple flows and analysis of nonslip boundary conditions for the lattice Boltzmann BGK model. J. Statist. Phys., 1997, 87(1-2): 115-136.
[23] Wang Dengwei, Li Chunrong, Shi Wenjun. Research on Laser Imaging Simulation and Multi-Dimensional Distinguishable Criterion Construction. Electronics Optics & Control (in Chinese), in press.