Fast Hybrid Level Set Model for Non-homogenous Image Segmentation
Solving by Algebraic Multigrid

Deng-wei WANG
School of Aeronautics and Astronautics, University of Electronic Science and Technology of China, Chengdu 611731, China

Keywords: Intensity inhomogeneity, Level set method, Segmentation, Algebraic multigrid.

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, and a special extra term that penalizes the deviation of the level set function from a signed distance function is also included in our method, so the complex and costly re-initialization procedure is completely eliminated. 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, the Algebraic Multigrid (AMG) is used for breaking the restrictions on time step, compared with the traditional schemes, the AMG strategy can shorten the time consumption of the evolution process, this allows the level set to quickly reach the true target location. The extensive and promising experimental results on numerous synthetic and real images have shown that our method can efficiently improve the image segmentation performance, in terms of accuracy, efficiency, and robustness.

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, Li et al. [13] proposed a local binary fitting (LBF) model, it utilizes the local region information and thus can provide accurate segmentation results. However, the final convergence result of the LBF model is related to the initial position of the curve, this means that LBF 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 LBF 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 LBF 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.

It is well known that under the level set framework, the problem of image segmentation can be mathematically transformed into a partial differential equation or linear system by means of variational methods and explicit and implicit numerical schemes. In the field of solving linear equations, a highly efficient multi-resolution scheme, named algebraic multigrid (AMG) [15] strategy, has emerged in the past research of mathematics. The algebraic multigrid is independent of the geometrical properties of the problem to be solved, and it uses only the information of the system itself to solve the linear equations, allowing the solution on unstructured grids, making it easier to extend to areas such as image processing. In view of the aforementioned advantages, we use the AMG scheme to solve our level set equation.

The remainder of this paper is organized as follows. Section 2 is a brief description of the classical C-V and LBF 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.

Background

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:

\[
E(C, M_{\text{in}}, M_{\text{out}}) = \lambda_1 \int_{\text{int}(C)} (I - M_{\text{in}})^2 \, dx\,dy + \lambda_2 \int_{\text{out}(C)} (I - M_{\text{out}})^2 \, dx\,dy + \mu \cdot L(C) + \nu \cdot S\left(\text{in}(C)\right)
\]  

(1)

where \( \mu, \nu, \lambda_1 \) and \( \lambda_2 \) are positive constants, we generally choose the parameters as follows: \( \lambda_1 = \lambda_2 = 1, \nu = 0 \). \( M_{\text{in}} \) and \( M_{\text{out}} \) 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 \( \phi(x, y): \Omega \to \mathbb{R} \), 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 \(\text{Energy}(C, M_{in}, M_{out})\) can be reformulated in terms of the level set function \(\phi(x, y)\) as follows:

\[
E_{c}(C, M_{in}, M_{out}) = \lambda_{c} \int_{\Omega} (1 - M_{in}) \hat{H}_{\epsilon} (\phi) dxdy + \\
\lambda_{s} \int_{\Omega} (1 - M_{out}) \hat{H}_{\epsilon} (\phi) dxdy + \mu \int_{\Omega} \delta_{\epsilon} (\phi) \nabla \phi dxdy + \nu \int_{\Omega} H_{\epsilon} (\phi) dxdy
\]

where \(H_{\epsilon}(z)\) and \(\delta_{\epsilon}(z)\) are, respectively, the regularized approximation of Heaviside function \(H(z)\) and the one-dimensional Dirac measure \(\delta(z)\) which are defined as follows:

\[
H(z) = \begin{cases} 
1, & \text{if } z \geq 0 \\
0, & \text{if } z < 0
\end{cases}
\]

\[
\delta(z) = \frac{d}{dz} H(z)
\]

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):

\[
\frac{\partial \phi}{\partial t} = \delta_{\epsilon}(\phi) \left[ \mu \text{div} \left( \frac{\nabla \phi}{\| \nabla \phi \|} \right) - \nu - \lambda_{1} (I - M_{in})^{2} + \lambda_{2} (I - M_{out})^{2} \right]
\]

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

\[
M_{in}(\phi) = \frac{\int_{\Omega} I \cdot H_{\epsilon}(\phi) dxdy}{\int_{\Omega} H_{\epsilon}(\phi) dxdy}, \quad M_{out}(\phi) = \frac{\int_{\Omega} (1 - H_{\epsilon}(\phi)) dxdy}{\int_{\Omega} (1 - H_{\epsilon}(\phi)) dxdy}
\]

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.

**LBF Model**

Chunming Li 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:

\[
E_{LBF}^{LBF} = \mu_{f} \int_{\Omega_{in}(C)} \int_{\Omega_{out}(C)} K_{\sigma}(x-y) \left| I(y) - f_{1}(x) \right|^{2} dy dx + \mu_{f} \int_{\Omega_{in}(C)} \int_{\Omega_{out}(C)} K_{\sigma}(x-y) \left| I(y) - f_{2}(x) \right|^{2} dy dx
\]

where \(I\) is the input image, \(\mu_{f}\) and \(\mu_{s}\) are control parameters, \(K_{\sigma}\) is a Gaussian kernel function with standard deviation equals to \(\sigma\), \(f_{1}\) and \(f_{2}\) are two fitting functions which approximate the local image pixel values inside and outside the contour \(C\) respectively.

Similar to the C-V model, we still describe the LBF model in the level set framework and use \(\phi\) to represent the level set function. Minimizing the energy functional \(E_{LBF}^{LBF}\) with respect to \(\phi\) by using the calculus of variation and the steepest descent method, we can easily deduce the corresponding gradient descent flow as:
\[
\frac{\partial \phi}{\partial t} = -\delta_x(\phi)(\mu e_1 - \mu e_2)
\]

(7)

e_1 \text{ and } e_2 \text{ in Eq. (8) are defined as:}

\[
e_1(x) = \int_a K_x(y-x)I(x-f_i(y)) \, dy, e_2(x) = \int_a K_x(y-x)I(x-f_j(y)) \, dy
\]

(8)

With

\[
f_i(x) = \frac{K_x * [H_x(\phi)I(x)]}{K_x * [1 - H_x(\phi)]}, f_j(x) = \frac{K_x * [1 - H_x(\phi)I(x)]}{K_x * [1 - H_x(\phi)]}
\]

(9)

In the above equations, we actually use the regularized versions of Heaviside function \( H \) and Dirac function \( \delta \) which are expressed as follows:

\[
H_x(z) = \frac{1}{2} \left[ 1 + \frac{2}{\pi} \arctan \left( \frac{z}{\varepsilon} \right) \right], \delta_x(z) = \frac{1}{\pi \varepsilon} \frac{\varepsilon}{\varepsilon^2 + z^2}, z \in \mathbb{R}
\]

(10)

The parameter \( \varepsilon \) affects the profile of \( \delta_x(\phi) \). A bigger \( \varepsilon \) 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 binary image \((\mu e_1 - \mu e_2)\) is based on all the pixels in a local Gaussian window, this localization property is the real reason for the LBF model to be able to segment non-homogenous images. However, when the contour is located at a certain location where \( \mu e_1 = \mu e_2 \), 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.

The Proposed Model

The Formulation of the Proposed Model

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

\[
E_{\text{local-global}}(\phi, M_{\text{in}}, M_{\text{out}}, e_1, e_2) = (1 - \beta) E^{\text{LBF}} + \beta \left( \lambda_1 \int_{\Omega} (I - M_{\text{in}})^2 H_x(\phi) \, dx \, dy + \lambda_2 \int_{\Omega} (I - M_{\text{out}})^2 (1 - H_x(\phi)) \, dx \, dy \right)
\]

(11)

where \( \beta \) 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 [16], characterized by the following energy functional:

\[
P(\phi) = \frac{1}{2} (|\nabla \phi(x)| - 1)^2 \, dx.
\]

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:

\[
L(\phi) = \int |\nabla H(\phi(x))| \, dx.
\]

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

\[
E_{\text{total}} = E_{\text{local-global}} + \eta P(\phi) + \mu L(\phi)
\]

(12)

where \( \eta \) and \( \mu \) are control parameters to balance the contribution of each energy term.

Keeping \( M_{\text{in}} \) and \( M_{\text{out}} \) fixed, and minimizing the entire energy functional \( E_{\text{total}} \) with respect to \( \phi \), we deduce the associated Euler–Lagrange equation for \( \phi \) as follows:
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 LBF 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 $\beta$ so that the new hybrid model can have the advantages of the C-V model and the LBF model. Therefore, the proposed model can effectively deal with the intensity inhomogeneity, regardless of the initial contour starting at the image.

The parameter $\beta$ 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 $\beta$, 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 $\beta$ 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 LBF model. If we set the parameter $\beta$ in formula (11) to 1 and 0, our model will be degraded to the C-V model and LBF 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 LBF model in general.

The Implementation of the Proposed Model

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. (13), but due to the Courant-Friedreichs-Lewy (CFL) [17] 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.

Algebraic Multigrid Method for Accelerating the Evolution of the Curve. 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. In order to overcome this problem effectively, we adopt a multi-resolution thought-based partial differential equation solver called AMG [15] to reduce the number of iterations by using a larger time step.

According to the principle of finite difference scheme, through the matrix-vector expression, we can get the following general discretization formula:

$$\frac{\phi^{n+1} - \phi^n}{\Delta t} = A \cdot \phi^n + F(\phi^n)$$

where $A \cdot \phi^n = \Gamma_{int}$, $F(\phi^n) = \Gamma_{ext} + \Gamma_{IFE}$.

Let us recall a simple spatial discretization of the internal term is a prerequisite for our semi-implicit scheme, setting $u := \frac{1}{\nabla \phi}$ the term $d_{iv} \left(\nabla \phi \right) \frac{\nabla \phi}{\nabla \phi}$ may be approximated as follows:
\[ \text{div}(u\nabla \phi) \approx \hat{\partial}_x \left( u_{ij} \frac{\phi_{i+1/2,j} - \phi_{i-1/2,j}}{h_x} \right) + \hat{\partial}_y \left( u_{ij} \frac{\phi_{i,j+1/2} - \phi_{i,j-1/2}}{h_y} \right) \]

\[ \approx \left[ u_{i+1/2,j} \frac{\phi_{i+1,j} - \phi_{i,j}}{h_x^2} - u_{i-1/2,j} \frac{\phi_{i-1,j} - \phi_{i,j}}{h_x^2} \right] + \left[ u_{i,j+1/2} \frac{\phi_{i,j+1} - \phi_{i,j}}{h_y^2} - u_{i,j-1/2} \frac{\phi_{i,j} - \phi_{i,j-1}}{h_y^2} \right] \]  

(15)

where \( h_x \) and \( h_y \) are the discrete grid sizes under the spatial finite difference mode, and are set here as \( h_x = h_y = h \). The value for \( u_{i+1/2,j} \) can be determined by linear interpolation as \( u_{i+1/2,j} \approx \left( u_{i,j} + u_{i,j+1} \right)/2 \) and use analogous expressions for the other similar terms. After number the pixels in a row-major order, we can get \( A = [a_{ij}] \), which is a \( N_{\text{image}} \times N_{\text{image}} \) (\( N_{\text{image}} = N_{\text{row}} \times N_{\text{col}} \) is the total number of pixels of the image) time-independent matrix with elements as:

\[ a_{ij} = \begin{cases} \frac{u_i + u_j}{2h^2}, & j \in N(i) \\ -\sum_{k \in N(i)} \frac{u_k + u_i}{2h^2}, & j = i \\ 0, & \text{otherwise} \end{cases} \]  

(16)

where \( N(i) \) denotes the 4-neighborhood of pixel \( i \).

Although Equation (14) is a simple explicit form, the existence of CFL condition \[17\] leads to its time step variable \( \Delta t \) can only take a small value.

In order to overcome the problem of the above explicit scheme, we use the following semi-implicit scheme:

\[ \frac{\phi^{n+1} - \phi^n}{\Delta t} = A^o \cdot \phi^{n+1} + F(\phi^n) \]  

(17)

The above scheme is unconditionally stable (see Ref. \[18\] for the detailed proof information) no matter how large the time step \( \Delta t \) is.

In each iteration, we need to solve the following linear system:

\[ \left( \frac{1}{\Delta t} E - A^o \right) \phi^{n+1} = A \phi^n = \frac{1}{\Delta t} \phi^n + F(\phi^n) = f \]  

(18)

where \( A = \frac{1}{\Delta t} E - A^o \) is a system matrix with a large size, thus it will undoubtedly increase the computational burden of the solution process. According to the symbols in the above expression, we further simplify it as

\[ A \phi = f \]  

(19)

To solve such a big linear system, simple iterative methods such as Jacobi or Gauss-Seidel are inefficient. Specifically, the iterations of these iterative methods required is proportional to the aforementioned variable \( N_{\text{image}} \). Since the computational complexity of one iteration of these iterative methods is also \( O\left( N_{\text{image}} \right) \), this leads to a \( O\left( N_{\text{image}}^2 \right) \) cost for each iteration of (14). For practical applications, such a high computational cost is unbearable.

In this paper, we use the AMG to solve equation (14), the reason is that the scheme can solve the linear system efficiently. The algebraic multigrid method includes the following two steps: the fine grid smoothing process and the coarse grid correction process. The smoothing process can quickly
remove the high-frequency components, while the coarse mesh correction process can help to correct those smoothed low-frequency components, through repeated iterations to achieve fast and accurate treatment of the problem.

AMG is a multilevel technique for solving large-scale linear systems with optimal or near-optimal efficiency. Unlike geometric multigrid, AMG requires little or no geometric information about the underlying problem and develops a sequence of coarser grids directly from the input matrix. This feature is especially convenient for the problems discretized on structured meshes such as the proposed hybrid fitting energy-based level set model. Figure 1 shows a generic two-level multigrid corresponding to the linear system shown in equation (14), where the superscript \( (\cdot)^h \) denotes fine grid quantities while the \( (\cdot)^{2h} \) denotes coarse grid quantities, \( R \) and \( P \) are the restriction operator and the prolongation operator, respectively. Firstly, we input the system matrix corresponding to the finest grid \( h^h A \). Then, the matrices for the coarser grid \( A^{2h} \) and the intergrid transfer operators \( R \) and \( P \) are computed automatically. Finally, the updated level set function \( \phi \) is generated through the coarse grid correction procedure. From Figure 1 we further see that the coarse grid size is irregular because the algebraic multigrid method constructs the coarse mesh sequence according to the coefficient matrix of the problem.

Since AMG allows large time step and fuses the fine mesh smoothing and coarse mesh correction ideas cleverly, only needs a small number of iterations can reach the final convergence state. In addition, AMG has a high degree of parallelization characteristics, therefore, we can implement it in parallel hardware architecture such as GPU, in order to further enhance its adaptability to big data.

![Figure 1. Generic two-level multigrid.](image1.png)

![Figure 2. 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.](image2.png)

**Algorithm of the Fast Hybrid Level Set Method for Image Segmentation.** The aforementioned two strategies can effectively overcome the problems of high computational complexity in traditional level set methods. Our fast hybrid level set algorithm (with the aforementioned acceleration strategies as traction) for non-homogenous image segmentation is performed as follows:

1. Initialize the level set function \( \phi \) as a signed distance function.
2. ①Compute \( M_{in}, M_{out}, e_1 \), and \( e_2 \) using (5) and (8), respectively; ②Compute \( \phi^n \) and \( f \) according to (18); ③Determine \( \phi^{n+1} \) according to (19) solving by AMG; ④Update the label map array of zero level set function based on \( \phi^{n+1} \).
3. Return step (2) until the evolution process reaches the state of convergence.
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 by Matlab R2012a on a computer with 2.3G Intel Core i7 CPU, 8G RAM, and Windows 7 operating system.

Comparisons with the C-V Model

Figure 2 shows the comparisons of segmentation result between our model and the C-V model on three images, the intensity non-homogeneity in these images is very significant, among them, the first row is a synthetic image, the second to the third rows are laser distance images (the simulation principle as shown in literature [21]). 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.

Comparisons with the LBF Model

In order to verify the initial contour position-insensitive characteristic (please refer to section 3.3. 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 Figure 3.

Figure 3 (a) shows the initial contours which have different shapes and initial positions. Figure 3 (b) and Figure 3 (c) show the final locations of the evolution curve by the LBF model and our model, respectively. From the final segmentation results we found that the outputs of LBF model under three initial conditions are not ideal and some of them even has a serious mistake, 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.

Fast Evolution Characteristics

In this section, we evaluate the acceleration performance of the AMG strategy used in this paper. The test images used here are the same as the images shown in Figure 2 to Figure 3. 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 AMG strategy (LGD+AMG). Table 1 shows the comparison results of time cost between the above methods, the sizes of the tested images are also listed. For the image shown in Figure 3, we take the mean value of the segmentation results.

According to the comparison results, we can deduce the following conclusions: The AMG can decrease the number of iterations of the evolution process and reduce the total CPU time by several times, this is undoubtedly very valuable in practical engineering applications.

Conclusions

This paper presents a fast hybrid level set algorithm for 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. A large number of experimental results show that our model can accurately segment the image with nonhomogeneous properties, and the final segmentation results are independent of the initial position of the initial curve. By analyzing the reason for high computational complexity, one corresponding strategy named AMG is induced to resolve it. The advantage of AMG is that its iterative time step is unrestricted, therefore, it can greatly reduce the time consumption of evolution process. Experiments are conducted to illustrate the speedup of the AMG strategy, and the results show that the proposed fast hybrid level set algorithm can reduce the total CPU time by several times. Because the AMG is very suitable for parallel implementation, our future works can be an implementation of the proposed method using a parallel device such as the GPU in order to fully take advantage of the AMG method.

<table>
<thead>
<tr>
<th>Input image</th>
<th>Algorithm</th>
<th>Iterations</th>
<th>CPU time (s)</th>
<th>Accelerated rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>The first row of column (a) of Figure 2 (127×96 pixels)</td>
<td>LGD</td>
<td>80</td>
<td>4.029</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>LGD+AMG</td>
<td>35</td>
<td>1.920</td>
<td>2.1</td>
</tr>
<tr>
<td>The second row of column (a) of Figure 2 (146×146 pixels)</td>
<td>LGD</td>
<td>50</td>
<td>2.951</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>LGD+AMG</td>
<td>21</td>
<td>1.341</td>
<td>2.2</td>
</tr>
<tr>
<td>The third row of column (a) of Figure 2 (95×95 pixels)</td>
<td>LGD</td>
<td>130</td>
<td>6.222</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>LGD+AMG</td>
<td>60</td>
<td>2.489</td>
<td>2.5</td>
</tr>
<tr>
<td>The first row of Figure 3 (118×93 pixels)</td>
<td>LGD</td>
<td>172</td>
<td>13.474</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>LGD+AMG</td>
<td>70</td>
<td>5.858</td>
<td>2.3</td>
</tr>
</tbody>
</table>

Acknowledgement

This work is supported by the Project of the Fundamental Research Funds for the Central Universities under Grant No. ZYGX2015KYQD032.

References


