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IMAGE SEGMENTATION USING FAST IMPLEMENTATION OF LEVEL SET WITHOUT RE-INITIALIZATION

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Abstract. *The level set method is one of the numerical algorithms for segmentation objects in medical images. Unfortunately, the standard level set method in which initialization is needed for every step (re-initialization process), makes further computational time during the process of searching boundary curves. It is necessary for medical technologist to obtain faster computational method for image segmentation. Hence, it is an important issue to decrease the computational time during the re-initialization process. On the other hand, there is another approach for fast computing technique using Message Passing Interface (MPI). This paper presents a fast level set method without re-initialization for medical CT images segmentation by developing computer program through MPI. This level set formulation is relied on three approaches including penalizing term, weighted length term and weighted area term. In this investigation, penalizing term is provided to avoid the time-consuming problem in the re-initializing process. By comparing with the standard program, our numerical results show that the proposed method is faster and more effective for image segmentation. The computational time is reduced with the same accuracy.*

Keywords: Image segmentation, Level set, Re-initialization, MPI

1. **Introduction.** Image segmentation has been expressed various problems including tumor segmentation, shape analysis and diagnosis of some diseases. Its objective is to separate a given image into the essential segments that are more useful and simpler to determine. There are many segmentation approaches such as region growing, active contour, level set, graph cuts, and clustering. The level set method is a crucial method which is precise and robust model to solve problems of surface evolution. Up to now, further development of level set method and their important applications have been demonstrated in image processing [1-4], computational physics [5,6], and fluid dynamics [7,8], etc. The level set method has been developed widely in medical imaging from different modalities [9,10]. Due to large size of the medical image data, it is more reasonable for generating an extremely fast level set computation to provide early diagnosis of the disease for surgical preparation and improve the survival rate.

Level set method proposed by Osher and Sethian [11] is one of popular computational techniques for tracking the evolution of curve. The moving contour is defined to be the zero level of the level set function. The level set's algorithm has been developed basing on numerically solving the Hamilton-Jacobi equations. Therefore, hyperbolic conservation law's theories can be used to support the algorithms. The advantage of level set method is that the representing contour can change their topology such as splitting or merging curves. The algorithm can be extended to three or higher dimensions, as well. Moreover, intrinsic geometric properties of the contour are easily calculated directly from the level set function. However, the level set method has a drawback. It is required the level set function to be a smoothed function over the entire domain. Thus, the level set function must be re-initialized regularly. As a result, the computational cost is high.

The re-initialization process is necessary in order to preserve stability of curve evolution, and to provide the expected shape [12]. The level set function must be re-initialized to be a signed distance function for a closed contour separating the curve into two regions. However, this re-initialization consumes more computational time. It is also difficult to accurately keep the location of the zero level set during the re-initialized process. Li et al. [13] modified these difficulties to avoid re-initialization procedure by adding a penalty term. This penalty term will maintain the level set function to be a signed distance function. This developed method is straightforward and more efficient than the standard level set method.

Parallel computing can deal with large and complex problems. It has been used widely in many fields such as science, engineering, industrial and commercial fields. Parallel implementation is the computational scheme for dividing a large structure into several elements, and then solves them simultaneously on individual processors [14]. Message Passing Interface (MPI) is essential for developing and running parallel program. This model determines system of information exchange by sending and receiving messages. The Message Passing Interface has been developed in C and Fortran 90 languages. In 2006, Carracciuolo et al. [15] used PETSc, a software library based on MPI, to reduce CPU time in their research of integration of parallel components and image de-noising in 3-D echocardiography.

A sequential execution model based on a single-core microprocessor is implemented in most of medical imaging over the last decade [3,4]. Roy et al. [16] have used it for images with a variational level set-based curve evolution on MATLAB with a single core. However, this computer system is rather low-level and limiting further performance improvement in large amounts of computation. Nowadays, multiple processing using several cores has been affected on the image development community [17]. A parallel software module for image segmentation based on the Parallel Sparse Basic Linear Algebra Subprograms (PSBLAS), that allowed computations on GPUs, was proposed by D'Ambra and Filippone in [18]. Unfortunately, GPUs must be enforced by a parallel software industry. In our research, we consider multi-core approaches which are integrated of a few CPUs on laptop or desktop based on portability and efficiency. Each processor keeps its own memory in a parallel way. This approach has more computational capability on a development of parallel software.

In this paper, the main objective is the innovation of fast numerical program based on the level set without re-initialization, and MPI in medical imaging. We focus on the penalizing term to avoid the complexity of distance re-initialization. Moreover, we also generate the emphasis of weighted edge term and weighted region term to control the movement of interface. We attempt to parallelize the level set formulation for image segmentation through MPI routines by using an implicit Partial Differential Equation (PDE) iterative scheme. The performance of this modification through MPI is also evaluated.

This paper is organized as follows. In Section 2, we review the standard level set method and indicate the re-initialization process. Furthermore, the level set formulation without re-initialization is proposed as energy minimization for segmentation. The implementation of MPI and experimental results are shown in Section 3. The conclusion and future work are summarized in Section 4.

2. **Problem Statement and Preliminaries.** We consider the boundary of curves in two dimensions. The boundary moves in a normal direction with respect to an inside and outside region with a speed function F. In the level set method, $\phi(x,t) : R^3 \to R$ is the unknown time dependent level set function, and x is the position vector of the curve. The main idea is to model the front by the zero level set of the function ϕ, which is defined by $\Gamma(t) = \{x|\phi(x,t) = 0\}$. To obtain an equation of motion, we apply the chain rule to the following equation $\phi(x,t) = 0$, and we get

$$\phi_t + \nabla\phi(x,t) \cdot x'(t) = 0, \tag{1}$$

where $x'(t)$ is the velocity of a particle. The speed function F moves in the direction normal to itself, and the curvature of the front is $\kappa = \nabla \cdot (\nabla\phi/|\nabla\phi|)$. Thus, $F = x'(t) \cdot n$, where $n = \nabla\phi/|\nabla\phi|$ is the unit normal vector of the curve. Hence, the equation of motion for ϕ is given by

$$\phi_t + F|\nabla\phi| = 0. \tag{2}$$

This equation is known as "the level set equation" proposed by Osher and Sethian [11].

During the evolution, the re-initializations of the level set function are required. Sussman et al. [19] developed the re-initialization process to rebuild the level set function to be a signed distance function by solving the level set equation to the steady state. The signed distance function is given by

$$\phi(x,t) = \begin{cases} C, & \text{if } x \text{ is outside } \Gamma \\ 0, & \text{if } x \text{ is on } \Gamma \\ -C, & \text{if } x \text{ is inside } \Gamma \end{cases} \tag{3}$$

where $C = |x - x_c|$ is a constant, and x_c is a point on the boundary closest to x. Hence, the standard re-initialization equation is defined by

$$\phi_t = S(\phi_0)\left(1 - |\nabla\phi|\right) \tag{4}$$

where ϕ_0 is the general level set function needed to be re-initialized. $S(\phi_0)$ is a sign function defined as

$$S(\phi_0) = \frac{\phi_0}{\sqrt{\phi_0^2 + |\nabla\phi|^2 \Delta x^2}} \tag{5}$$

where Δx is the spatial distance [12]. However, the re-initialization process is still very expensive, and causes some undesirable solution. To avoid the re-initialization process, Li et al. [13] proposed a level set evolution equation without re-initialization based on an energy-minimizing model. An energy function of the level set function composes of an internal energy $E_{\text{int}}(\phi)$ and the external energy $E_{ext}(\phi)$. Thus, the energy function of the level set function is given by

$$E(\phi) = E_{\text{int}}(\phi) + E_{ext}(\phi). \tag{6}$$

The internal energy is related to the potential function. It is given by

$$E_{\text{int}} = \mu \int_{\Omega} p\left(|\nabla\phi|\right) dx \tag{7}$$

where $\mu > 0$ is a constant. For example, if $p = (s-1)^2/2$, then

$$E_{\text{int}} = \mu \int_{\Omega} \left(|\nabla\phi| - 1\right)^2 dx. \tag{8}$$

The internal energy function was introduced as a penalizing term in order to obtain the smoothness contour, and keep the level set function to be a signed distance function. Due to the effect of the penalizing term, we can avoid the re-initializing process. As a result, we can reduce the computation cost. The external energy, which drives the motion of curve to the object boundary, is defined as

$$E_{ext}(\phi) = \lambda \int_\Omega g\delta(\phi) |\nabla \phi| \, dx + \alpha \int_\Omega gH(-\phi)dx \tag{9}$$

where $\lambda > 0$ and α are fixed parameters, δ is the Dirac function, and H is the Heaviside function. We assume that I is an input image on a domain Ω, and g is the edge indicator function given by

$$g = \frac{1}{1 + |\nabla(G_\sigma * I)|^2} \tag{10}$$

where $G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$ is the Gaussian smoothing filter with standard deviation σ.

The Dirac delta function $\delta(\phi)$ is

$$\delta(\phi) = \begin{cases} 0, & |\phi| > \varepsilon \\ \dfrac{1}{2\varepsilon}\left(1 + \cos\left(\dfrac{\pi\phi}{\varepsilon}\right)\right), & |\phi| \le \varepsilon \end{cases} \tag{11}$$

where $\varepsilon = 1.5(\Delta x)$ is defined as the width of the boundary [19]. A gradient flow is a suitable way to minimize the energy function. Based on the calculus of variations, the modified level set formulation is defined as

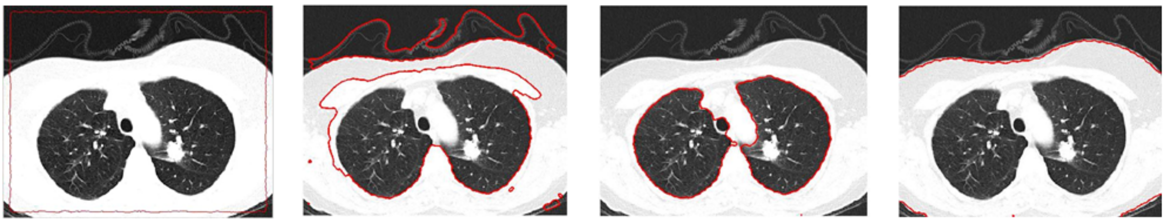
$$\frac{\partial \phi}{\partial t} = -\frac{\partial E}{\partial \phi} = \mu\left(\Delta\phi - \left(div\frac{\nabla\phi}{|\nabla\phi|}\right)\right) + \lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + \alpha g\delta(\phi) \tag{12}$$

where Δ is called the Laplacian operator. The second term in (12) is called the weighted length term calculating the length of the zero level curves. The third term is called the weighted area term controlling the speed of the evolution curve. The last two terms are provided the zero level curves moving to the object boundaries. If the initial contour is outside the object, the parameter α is taken as positive value. On the other hand, if the initial contour is inside the object, then the parameter α is taken as negative value. To optimize the Gaussian kernel standard deviation σ, we use the Gaussian kernel size N based on 3-σ rule in statistics for smoothing image as

$$3\sigma \sim (N/2 - 1) + (1 + \varepsilon). \tag{13}$$

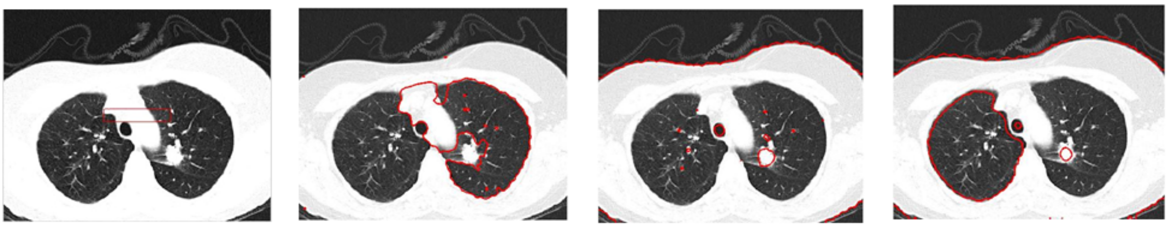
The Gaussian kernel size is always a positive odd number. In this case, we use the kernel size $N = 15$ with $\varepsilon = 1.5$ to obtain the expected contour in our experiment. The value of the Gaussian kernel standard deviation in the experiment is taken as $\sigma = 3.0$.

3. **Main Results.** Our experiment has been performed on a computer with Intel Core (TM) i7, 2.90 GHz CPU, 8G RAM, and Windows 7 operating system. The MATLAB algorithm was done using lung cancer CT image with 314×394 pixel from online web [20]. The evolution of level set segmentation is applied to locate the boundary of cancer cell. In this paper, the initial contour is presented at three levels such as 4, 0 and -4. Figure 1 presents the evolution of curve with similar initial contour but different standard deviation σ. In this case, the parameter values $\mu = 0.04$, $\lambda = 5.0$ and $\alpha = 1.5$ are used with the time step $\Delta t = 5.0$ of each iteration. The initial contour is presented from the outside object as shown in Figure 1(a). Figures 1(b)-1(d) show the final contour with standard deviation $\sigma = 1.5, 3.0, 4.5$, respectively. The default standard deviation $\sigma = 1.5$ from the original paper [13] cannot obtain the accurate final curve. Therefore, we use the value $\sigma = 3.0$ based on 3-σ rule in statistics to increase the accuracy as shown in Figure 1(c). The evolution contour cannot detect the cancer cell as we expected. Therefore, we adjust the parameters that control the width of the initial level set curve. The parameters $\mu = 0.1$, $\lambda = 6.0$ and $\alpha = -3.0$ are used with the time step $\Delta t = 2.0$ to achieve a



(a) (b) (c) (d)

Figure 1. Segmentation results of lung cancer CT images by using MATLAB from outside the object. (a) The initial contour, (b) the final contour with $\sigma = 1.5$, (c) the final contour with $\sigma = 3.0$, and (d) the final contour with $\sigma = 4.5$



(a) (b) (c) (d)

Figure 2. Segmentation results of lung cancer CT images by using MATLAB from inside the object. (a) The initial contour, (b) the final contour with $\sigma = 1.5$, (c) the final contour with $\sigma = 3.0$, and (d) the final contour with $\sigma = 4.5$

desirable curve. Color contour is represented the initial level contour starting from inside the lung region as shown in Figure 2(a). The final level set contour of lung nodules for three different values of standard deviation $\sigma = 1.5, 3.0, 4.5$ with the same initial contour are shown in Figures 2(b)-2(d). As we have mentioned in Figure 1, the standard deviation $\sigma = 3.0$ based on 3-σ rule in statistics is indicated a high quality of lung cancer segmentation. Figures 3(a) and 3(b) show the evolution contour of all weighted term at first iteration by using MATLAB and parallel implementation. Figure 3(c) shows the computational time of our program comparing with MATLAB program to evaluate the efficiency. Our results demonstrate that our proposed method can perform the evolving curve of the total weighted term decreased by a factor of 5.3. Our parallel implementation is remarkably faster than the standard program with the same accuracy.

4. **Conclusions.** In this paper, we have performed a level set segmentation without using re-initialization to detect the lung region and cancer cell. By penalizing effect, the re-initialization process can be avoided in order to reduce the CPU time. Moreover, by using 3-σ rule in statistics, the parameters can be selected for higher accurate image segmentation. To improve the speed of computing, the evolving level set function is proposed by coding a program through MPI routines based on C language. Our experimental results have shown high performance of our program in terms of efficiency by decreasing the CPU time. In our future work, we will develop a computer program to simulate the zero level curves at different times and support multiple processors. In addition, our code will be implemented to multiple inputting images.

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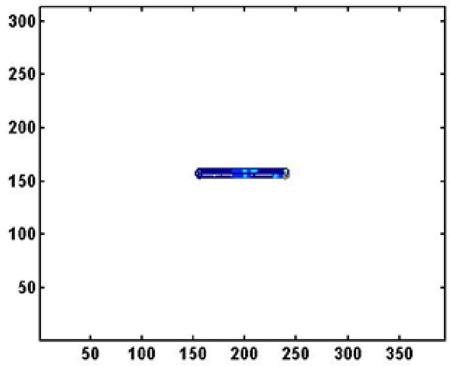
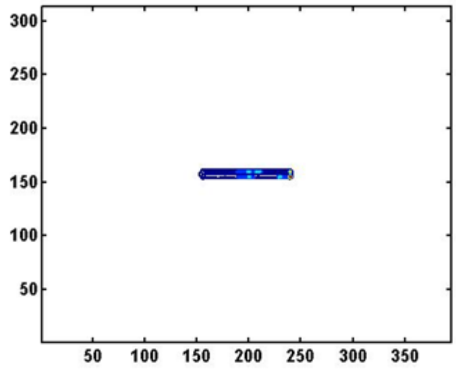
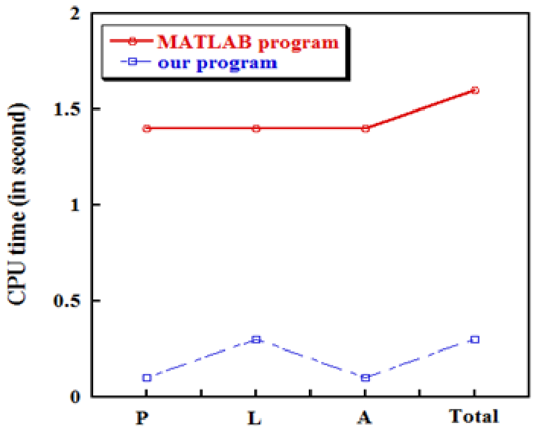


(a)



(b)



(c)

FIGURE 3. Effect of parallel implementation. (a) The contour of all weighted term at first iteration by MATLAB code, (b) the contour of all weighted term at first iteration by parallel implementation, and (c) comparison of our program and MATLAB program in terms of CPU time

REFERENCES

[1] C. Li, R. Huang, Z. Ding, C. Gatenby, D. N. Metaxas and J. C. Gore, A level set method for image segmentation in the presence of intensity inhomogeneities with application to MRI, *IEEE Trans. Image Process*, vol.20, no.7, pp.2007-2016, 2011.

[2] Z. Ren, Adaptive active contour model driven by fractional order fitting energy, *Signal Processing*, vol.117, pp.138-150, 2015.

[3] Y. Wang, S. M. Xiang, C. H. Pan, L. F. Wang and G. F. Meng, Level set evolution with locally linear classification for image segmentation, *Pattern Recognit.*, vol.46, no.6, pp.1734-1746, 2013.

[4] T. Wang, H. Wang and L. Fan, A weakly supervised geodesic level set framework for interactive image segmentation, *Neurocomputing*, vol.168, pp.55-64, 2015.

[5] F. Sanchez, L. Domenech, V. Garcia, N. Montes, A. Falco, E. Cueto, F. Chinesta and P. Fideu, Fast and reliable gate arrangement pre-design of resin infusion processes, *Composites Part A: Applied Science and Manufacturing*, vol.77, pp.285-292, 2015.

[6] K. Yokoi, A density-scaled continuum surface force model within a balanced force formulation, *Journal of Computational Physics*, vol.278, pp.221-228, 2014.

[7] C.-J. Huang, C.-Y. Lin and C.-H. Chen, Numerical simulations of fluid-structure interaction based on Cartesian grids with two boundary velocities, *Int. J. Numer. Meth. Fluids*, vol.73, no.3, pp.138-161, 2015.

[8] Y. Sen, Y. Qian, A. Avolio and M. Morgan, Image segmentation methods for intracranial aneurysm haemodynamic research, *Journal of Biomechanics*, vol.47, no.7, pp.1014-1019, 2014.

[9] S. Taheri, S. H. Ong and V. F. H. Chong, Level-set segmentation of brain tumor using threshold-based speed function, *Image Vis. Comput.*, vol.28, pp.26-37, 2010.

[10] K. Thapaliyaa, J.-Y. Pyuna, C.-S. Parkb and G.-R. Kwona, Level set method with automatic selective local statistics for brain tumor segmentation in MR images, *Computerized Medical Imaging and Graphics*, vol.37, nos.7-8, pp.522-537, 2013.
[11] S. Osher and J. A. Sethian, Fronts propagating with curvature dependent speed: Algorithms based on Hamilton-Jacobi formulations, *Journal of Computational Physics*, vol.79, pp.12-49, 1988.
[12] D. Peng, B. Merriman, S. Osher, H. Zhao and M. Kang, A PDE-based fast local level set method, *Journal of Computational Physics*, vol.155, no.2, pp.410-438, 1999.
[13] C. Li, C. Xu, C. Gui and M. D. Fox, Level set evolution without re-initialization: A new variational formulation, *Proc. of IEEE Conf. Comput. Vis. Pattern Recognit.*, vol.1, pp.430-436, 2005.
[14] W. Subber and A. Sarkar, A domain decomposition method of stochastic PDEs: An iterative solution techniques using a two-level scalable preconditioner, *Journal of Computational Physics*, vol.257, pp.298-317, 2014.
[15] L. Carracciuolo, L. D'Amore and A. Murli, Towards a parallel component for imaging in PETSc programming environment: A case study in 3-D echocardiography, *Parallel Computing*, vol.32, no.1, pp.67-83, 2006.
[16] K. Roy, P. Bhattacharya and C. Y. Suen, Iris segmentation using variational level set method, *Optics and Lasers in Engineering*, vol.49, pp.578-588, 2011.
[17] J. Diaz, C. Munoz-Caro and A. Nino, A survey of parallel programming models and tools in the multi and many-core era, *IEEE Trans. Parallel and Distributed Systems*, vol.23, no.8, pp.1369-1386, 2012.
[18] P. D'Ambra and S. Filippone, A parallel generalized relaxation method for high-performance image segmentation on GPUs, *J. of Computational and Applied Mathematics*, vol.293, pp.35-44, 2016.
[19] M. Sussman, P. Smereka and S. Osher, A level set approach for computing solutions to incompressible two-phase flow, *J. Comp. Phys.*, vol.114, pp.146-159, 1994.
[20] P. Ward, *Tread Cautiously When It Comes to Lung CT Screening*, http://www.auntminnieeurope.com/index.aspx?sec=ser&sub=def&pag=dis&ItemID=607014.