Computers in Biology and Medicine 41 (2011) 1–10

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/cbm

Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation

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ARTICLE INFO

Article history:
Received 25 January 2010
Accepted 25 October 2010

Keywords:
Adaptive clustering
Medical image segmentation
Level set methods
Spatial fuzzy clustering

ABSTRACT

The performance of the level set segmentation is subject to appropriate initialization and optimal configuration of controlling parameters, which require substantial manual intervention. A new fuzzy level set algorithm is proposed in this paper to facilitate medical image segmentation. It is able to directly evolve from the initial segmentation by spatial fuzzy clustering. The controlling parameters of level set evolution are also estimated from the results of fuzzy clustering. Moreover the fuzzy level set algorithm is enhanced with locally regularized evolution. Such improvements facilitate level set manipulation and lead to more robust segmentation. Performance evaluation of the proposed algorithm was carried on medical images from different modalities. The results confirm its effectiveness for medical image segmentation.

1. Introduction

The underlying objective of medical image segmentation is to partition it into different anatomical structures, thereby separating the components of interest, such as blood vessels and liver tumors, from their background. Computerized medical image segmentation is a challenging problem, due to poor resolution and weak contrast. Moreover the task is often made more difficult by the presence of noise and artifacts, due to instrumental limitations, reconstruction algorithms and patient movement. There is yet no universal algorithm for medical image segmentation. An algorithm's advantages and drawbacks often vary according to the problem under investigation.

The outcomes of most medical imaging modalities are of gray scale intensities. Suppose a medical image $\mathbf{I}(x,y)$, where $x(\in[1,N_x])$ and $y(\in[1,N_y])$ are spatial indices, and the pixel $i(x,y)$ quantifies the corresponding intensity. Image segmentation is to find a set of meaningful subclasses $\mathbf{S}_k$, where

$$\cup\mathbf{S}_k=\mathbf{I};\tag{1}$$

$$\mathbf{S}_k\cap\mathbf{S}_j=\emptyset.\tag{2}$$

The indices k and j lie in the interval $[1,K]$ and K is the number of subclasses. Eq. (1) claims that an image segmentation should be complete, while Eq. (2) requires it to be non-overlapping.

There are two well-established concepts in image segmentation: pixel classification and tracking variational boundary [1]. The first one assumes that the pixels in each subclass have nearly constant intensities, which is true for the anatomical structures with similar physiological properties. Such algorithms may detect multiple components concurrently, but they are susceptible to environmental noise and image inhomogeneity. In contrast, methods that track variational boundaries make use of both intensity and spatial information. Therefore, a subclass has to be homogeneous and enclosed in a specific variational boundary. When applied to medical image segmentation, neither of them is universally robust due to intrinsic noise and artifacts [1–5].

Most segmentation algorithms in practice require radiologists, with their experience and knowledge, to adjust the segmentation parameters carefully for an optimal performance. Due to the complexity of medical image segmentation, most computerized systems run in a semi-automatic or interactive manner [6]; the radiologists initiate the segmentation, interrupt it when necessary, and finally stop the algorithm. Obviously such a procedure is quite subjective and labor-intensive. As a consequence, the ease of manipulation often determines the acceptance of a segmentation algorithm in clinics [7–9].

Level set methods, which are established on dynamic implicit interfaces and partial differential equations (PDEs), have been shown to be effective for medical image segmentation [9–11].

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doi:10.1016/j.compbiomed.2010.10.007

However to employ those methods, clinical radiologists and even engineering practitioners are often overwhelmed by intensive computational requirements and complex regulation of controlling parameters [12]. Current state-of-the-art research is therefore oriented to facilitating the manipulation, while enhancing the quality of segmentation [7,10,12–14].

There have been many hybrid intelligent systems using fuzzy clustering to facilitate level set segmentation [9,10,13,14]. In short, such algorithms employ fuzzy clustering, based on an image intensity, for initial segmentation and employ level set methods for object refinement by tracking boundary variation. Our previous work on liver tumor segmentation [9] has shown that, fuzzy clustering, by approximately delineating tumor boundaries, not only relieves manual intervention, but also accelerates level set optimization. Ho and Suri, on the other hand, proposed to regularize level set evolution locally by fuzzy clustering, in order to alleviate the problems of noise sensitivity and weak boundaries [10,13,14]. Nevertheless, the operators still have to set several parameters carefully for an optimal level set segmentation.

In this paper, we propose a new fuzzy level set algorithm for automated medical image segmentation. Compared to our previous method [9], the new algorithm is significantly improved in the following aspects. Firstly, fuzzy clustering incorporates spatial information during an adaptive optimization, which eliminates the intermediate morphological operations. Secondly, the controlling parameters of level set segmentation are now derived from the results of fuzzy clustering directly. Thirdly, a new strategy, directed by fuzzy clustering, is proposed to regularize level set evolution, which is different from other methods [10,13,14]. Finally, we also verified the new fuzzy level set algorithm on general medical images, for example, ultrasound, computed tomography (CT) and magnetic resonance imaging (MRI).

The remainder of this paper is organized as follows. The next section describes fuzzy clustering and the algorithm with spatial restrictions. Section 3 elaborates on level set segmentation and a fast algorithm. Section 4 presents the new fuzzy level set algorithm in detail. Section 5 reports our experiments and the relevant discussion. Concluding remarks are drawn in Section 6.

2. Spatial fuzzy clustering and image segmentation

In fuzzy clustering, the centroid and the scope of each subclass are estimated adaptively in order to minimize a pre-defined cost function. It is thereby appropriate to take fuzzy clustering as a kind of adaptive thresholding. Fuzzy *c*-means (FCM) is one of most popular algorithms in fuzzy clustering, and has been widely applied to medical problems [4,5,15].

The classical FCM algorithm originates from the *k*-means algorithm. In brief, the *k*-means algorithm seeks to assign N objects, based on their attributes, into K clusters ($K \le N$). For medical image segmentation, N equals the number of image pixels $N_x \times N_y$. The desired results include the centroid of each cluster and the affiliations of N objects. Standard *k*-means clustering attempts to minimize the cost function

$$J = \sum_{m=1}^{K} \sum_{n=1}^{N} ||i_n - v_m||^2, \tag{3}$$

where i_n is the specific image pixel, v_m is the centroid of the mth cluster, and $||\cdot||$ denotes the norm. The ideal results of a *k*-means algorithm maximize the inter-cluster variations, but minimize the intra-cluster ones.

In *k*-means clustering, every object is limited to one and only one of K clusters. In contrast, an FCM utilizes a membership function μ_{mn} to indicate the degree of membership of the nth object to the mth cluster, which is justifiable for medical image segmentation as physiological tissues are usually not homogeneous. The cost function in an FCM is similar to Eq. (3)

$$J = \sum_{n=1}^{N} \sum_{m=1}^{C} \mu_{mn}^{l} ||i_n - v_m||^2, \tag{4}$$

where $l(>1)$ is a parameter controlling the fuzziness of the resultant segmentation. The membership functions are subject to the following constraints:

$$\sum_{m=1}^{C} \mu_{mn} = 1; \quad 0 \le \mu_{mn} \le 1; \quad \sum_{n=1}^{N} \mu_{mn} > 0. \tag{5}$$

The membership functions μ_{mn} and the centroids v_m are updated iteratively

$$\mu_{mn} = \frac{||i_n - v_m||^{-2/(l-1)}}{\sum_{k=1}^{C} ||i_n - v_k||^{-2/(l-1)}}; \tag{6}$$

$$v_i = \frac{\sum_{n=1}^{N} \mu_{mn}^{l} i_n}{\sum_{n=1}^{N} \mu_{mn}^{l}}. \tag{7}$$

The standard FCM algorithm is optimized when pixels close to their centroid are assigned high membership values, while those that are far away are assigned low values.

One of the problems of standard FCM algorithms in an image segmentation is the lack of spatial information [4,5,9]. Since image noise and artifacts often impair the performance of an FCM segmentation, it would be attractive to incorporate spatial information into an FCM. Cai et al. [5] proposed a generalized FCM algorithm that adopts a similarity factor to incorporate local intensity and spatial information. In contrast to the above preparatory weighting, it is also possible to utilize morphological operations to apply spatial restrictions at the post-processing stage [9].

Chuang et al. [4] proposed another spatial FCM algorithm in which spatial information can be incorporated into fuzzy membership functions directly using

$$\mu'_{mn} = \frac{\mu_{mn}^{p} h_{mn}^{q}}{\sum_{k=1}^{C} \mu_{kn}^{p} h_{kn}^{q}}, \tag{8}$$

where p and q are two parameters controlling the respective contribution. The variable h_{mn} includes spatial information by

$$h_{mn} = \sum\nolimits_{k \in N_n} \mu_{nk}, \tag{9}$$

where N_n denotes a local window centered around the image pixel n. The weighted μ_{mn} and the centroid v_m are updated as usual according to Eqs. (6) and (7).

3. Level set segmentation

In contrast to FCM using pixel classification, level set methods utilize dynamic variational boundaries for an image segmentation [16,17]. Segmenting images by means of active contours is a well-known approach [2,18,19], but instead of parametric characterization of active contours, level set methods embed them into a time-dependent PDE function $\phi(t,x,y)$. It is then possible to approximate the evolution of active contours implicitly by tracking the zero level set $\mathbf{\Gamma}(t)$

$$\begin{cases} \phi(t,x,y) < 0 & (x,y) \text{ is inside } \mathbf{\Gamma}(t) \\ \phi(t,x,y) = 0 & (x,y) \text{ is at } \mathbf{\Gamma}(t) \\ \phi(t,x,y) > 0 & (x,y) \text{ is outside } \mathbf{\Gamma}(t) \end{cases} \tag{10}$$

The implicit interface $\mathbf{\Gamma}$ may be comprised of a single or a series of zero isocontours. The issue of an image segmentation is therefore converted to

$$\cup \mathbf{S}_k \cup \mathbf{\Gamma} = \mathbf{I}. \tag{11}$$

Note that the inclusion of the time variable t leads to a higher-dimensional level set function ϕ, which incurs an additional computation, but has many practical advantages. For example, the interface $\mathbf{\Gamma}$ can be easily determined by checking the values of the level set function ϕ, which accommodates topological changes of the implicit interface $\mathbf{\Gamma}$ naturally. In particular, the evolution of ϕ is totally determined by the numerical level set equation

$$\begin{cases} \frac{\partial \phi}{\partial t} + F|\nabla\phi| = 0 \\ \phi(0, x, y) = \phi_0(x, y) \end{cases} \tag{12}$$

where $|\nabla\phi|$ denotes the normal direction, $\phi_0(x, y)$ is the initial contour and F represents the comprehensive forces, including the internal force from the interface geometry (e.g., mean curvature, contour length and area) and the external force from image gradient and/or artificial momentums [20,21].

The advancing force F has to be regularized by an edge indication function g in order to stop level set evolution near the optimal solution

$$g = \frac{1}{1+|\nabla(G_\sigma * \mathbf{I})|^2}, \tag{13}$$

where $G_\sigma * \mathbf{I}$ stands for the convolution of the image $\mathbf{I}$ with a smoothing Gaussian kernel G_σ, and ∇ denotes the operation for an image gradient. The function g is near zero in variational boundaries, but positive otherwise. A popular formulation for level set segmentation is [22]

$$\frac{\partial \phi}{\partial t} = g|\nabla\phi|\left(\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) + \nu\right), \tag{14}$$

where div $(\nabla\phi/|\nabla\phi|)$ approximates mean curvature κ and ν is a customable balloon force.

One of the biggest challenges in level set segmentation is the intensive computation. The level set function ϕ converts the 2D image segmentation problem into a 3D problem. There are other constraints for stable level set evolution, too. For instance, the time step and the grid space should comply with the Courant–Friedreichs–Lewy (CFL) condition [16,17], and the level set function ϕ should be re-initiated periodically as a signed distance function. In order to overcome these challenges, a fast level set formulation was proposed [23]

$$\frac{\partial \phi}{\partial t} = \mu\zeta(\phi) + \xi(g, \phi), \tag{15}$$

where the first term $\zeta(\phi)$ at the right side is a penalty momentum of ϕ, deviating from the signed distance function

$$\zeta(\phi) = \Delta\phi - \mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right). \tag{16}$$

The second term $\xi(g, \phi)$ incorporates an image gradient information by

$$\xi(g, \phi) = \lambda\delta(\phi)\mathrm{div}\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + \nu g\delta(\phi), \tag{17}$$

where $\delta(\phi)$ denotes the Dirac function. The constants μ, λ and ν control the individual contributions of these terms.

In essence, the term $\xi(g, \phi)$ attracts ϕ towards the variational boundary, which is similar to the standard level set methods. However, the penalty term $\zeta(\phi)$ forces ϕ to approach the genuine signed distance function automatically, which has important advantages. First, the new algorithm eliminates the computationally expensive re-initialization for signed distance functions. Second, it may start from an arbitrary binary region

$$\phi_0(x, y) = \begin{cases} -C, & \phi_0(x, y) < 0 \\ C, & \text{otherwise} \end{cases} \tag{18}$$

where C is a customable constant. Finally, it allows a larger time step τ, but still ensures stable evolution

$$\phi^{k+1}(x, y) = \phi^k(x, y) + \tau[\mu\zeta(\phi^k) + \xi(g, \phi^k)]. \tag{19}$$

The modifications lead to a fast level set algorithm for medical image segmentation. The speed improvement makes it easier to test and evaluate level set segmentation.

4. A new fuzzy level set algorithm

Both FCM algorithms and level set methods are general-purpose computational models that can be applied to problems of any dimension. However, if we constrain them to medical image segmentation, it is possible to take advantage of the specific circumstances for better performance. A new fuzzy level set algorithm is thereby proposed for an automated medical image segmentation. It begins with spatial fuzzy clustering, whose results are utilized to initiate level set segmentation, estimate controlling parameters and regularize level set evolution.

The new fuzzy level set algorithm automates the initialization and parameter configuration of the level set segmentation, using spatial fuzzy clustering. It employs an FCM with spatial restrictions to determine the approximate contours of interest in a medical image. Benefitting from the flexible initialization as in Eq. (18), the enhanced level set function can accommodate FCM results directly for evolution. Suppose the component of interest in an FCM results is $\mathbf{R}_k$: $\{r_k = \mu_{nk},\ n = x \times N_y + y\}$. It is then convenient to initiate the level set function as

$$\phi_0(x, y) = -4\varepsilon(0.5 - \mathbf{B}_k), \tag{20}$$

where ε is a constant regulating the Dirac function [17,23]. The Dirac function is then defined as follows:

$$\delta_\varepsilon(x) = \begin{cases} 0, & |x| > \varepsilon \\ \frac{1}{2\varepsilon}\left[1 + \cos\left(\frac{\pi x}{\varepsilon}\right)\right], & |x| \le \varepsilon \end{cases} \tag{21}$$

$\mathbf{B}_k$ is a binary image obtained from

$$\mathbf{B}_k = \mathbf{R}_k \ge b_0, \tag{22}$$

where $b_0(\in(0,1))$ is an adjustable threshold. Benefitted from spatial fuzzy clustering, $\mathbf{B}_k$ can in some sense approximate the component of interest, which can be readily adjusted by b_0.

There are several controlling parameters associated with level set methods (Table 1), all of which are important for medical image segmentation. It is therefore necessary to configure them appropriately, which unfortunately varies from case to case. Currently there are merely a few general rules to guide the configuration of these parameters. For example, it is known that a larger σ leads to a

Table 1
The parameters controlling level set segmentation.

Parameter	Significance
σ	Controlling the spread of Gaussian smoothing function
C	Controlling the gradient strength of initial level set function
ε	Regulator for Dirac function $\delta(\phi)$
μ	Weighting coefficient of the penalty term $\zeta(\phi)$
λ	Coefficient of the contour length for smoothness regulation
ν	Artificial balloon force
τ	Time step of level set evolution
T	Maximum iteration of level set evolution

smoother image, but sacrifices an image detail. A larger time step τ may accelerate level set evolution, but incurs the risk of boundary leakage. Moreover it is necessary to choose a positive ν if the initial ϕ_0 is outside the component of interest, and *vice versa*.

In addition, by trial and error, several rules of thumb have been suggested for an optimal level set segmentation [16,17,23]. For example, the product of the time step and penalty coefficient ($\tau \times \mu$) must be smaller than 0.25 for stable evolution, and the parameter C should be larger than 2ε, whilst too large a value of C slows the level set evolution down. It is also found in our practice that a larger λ often leads to smoother contours and a larger ν accelerates the level set evolution. However, there is a risk of boundary leakage. The above general guidelines, while useful, are insufficient to determine the optimal configuration for a specific medical image.

It is attractive to determine these controlling parameters adaptively for the specific medical image. Given the initial level set function ϕ_0 from spatial fuzzy clustering as in Eq. (20), it is convenient to estimate the length ℓ and the area α by

$$\ell = \int_I \delta(\phi_0)dx\,dy; \tag{23}$$

$$\alpha = \int_I H(\phi_0)dx\,dy, \tag{24}$$

where the Heaviside function $H(\phi_0)$ is

$$H(\phi_0) = \begin{cases} 1, & \phi_0 \geq 0 \\ 0, & \phi_0 < 0 \end{cases} \tag{25}$$

We observe that level set evolution will be faster if the component of interest is large. In this case, the ratio

$$\varsigma = \alpha/\ell \tag{26}$$

will also be large. It is thereby reasonable to assign the time step τ as ς in the proposed fuzzy level set algorithm. The penalty coefficient μ will be set as

$$\mu = 0.2/\varsigma \tag{27}$$

because their product ($\tau \times \mu$) should be less than 0.25 for stable evolution. The initial level set function ϕ_0 obtained from fuzzy clustering Eq. (20) will approximate the genuine boundaries. Therefore, a comparatively conservative λ

$$\lambda = 0.1\varsigma \tag{28}$$

is used to control topological changes.

The balloon force ν undertakes two roles in the level set evolution. First, its sign determines the advancing direction of the level set function: positive for shrinkage and negative for expansion. Second, the larger ν is, the faster the level set evolves. In standard level set algorithms, the controlling parameter ν is often set as a global constant. Nevertheless, it is obviously advantageous to make the level set function evolve faster, if ϕ is still far away from the genuine boundary. On the contrary, the level set function should have been slow down once ϕ approaches that boundary. Moreover the level set function should alter its direction automatically, while passing through the boundary of interest. We found the initial FCM segmentation, as a quantitative index, is particularly useful to regularize level set evolution.

The new fuzzy level set algorithm takes the degree of membership of each image pixel μ_k as the distance to the specific component of interest $\mathbf{R}_k$. An enhanced balloon force is proposed here to pull or push the dynamic interface adaptively towards the object of interest:

$$G(\mathbf{R}_k) = 1 - 2\mathbf{R}_k. \tag{29}$$

The resultant balloon force $G(\mathbf{R}_k)$ ($\in [-1, 1]$) is a matrix with a variable pulling or pushing force at each image pixel. In other words, the level set function will be attracted towards the object of interest regardless its initial position. Then, the evolutionary equation (Eq. (17)) is transformed into

$$\xi(g, \phi) = \lambda\delta(\phi)\mathrm{div}\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + gG(\mathbf{R}_k)\delta(\phi). \tag{30}$$

The proposed enhancement achieves several practical benefits. The balloon force can now be derived from spatial fuzzy clustering directly. Moreover level set evolution is now adapted to the distance to the genuine object. Once approaching the object, the level set function will automatically slow the evolution down and will become totally dependent on the smoothing term. Since a conservative λ is adopted here, level set evolution stabilizes automatically. An additional benefit is the flexibility to choose a comparatively large iteration of evolution T for robust segmentation. Without such an enhancement, the operator has to keep an alert to the level set evolution in order to avoid insufficient or excessive segmentation [7].

5. Experiments and discussion

The experiments and performance evaluation were carried on medical images from different modalities, including an ultrasound image of the carotid artery [24], a CT scan of liver tumors [9] and an MRI slice of cerebral tissues [25]. Both algorithms of spatial FCM and the proposed fuzzy level set method were implemented with Matlab® R2007b (MathWorks, Natick, MA) in a Windows® XP system (Microsoft, Redmond, WA). All the experiments were run on a Dell® Precision 340 computer with Pentium® 4 CPU 2.53 GHz and 1 GB RAM.

The first experiment was designed to evaluate the usefulness of an initial fuzzy clustering for level set segmentation. It adopted the fast level set algorithm as in references [23,24] for the curve optimization, where the initialization was by manual demarcation, intensity thresholding and spatial fuzzy clustering. Fig. 1 depicts

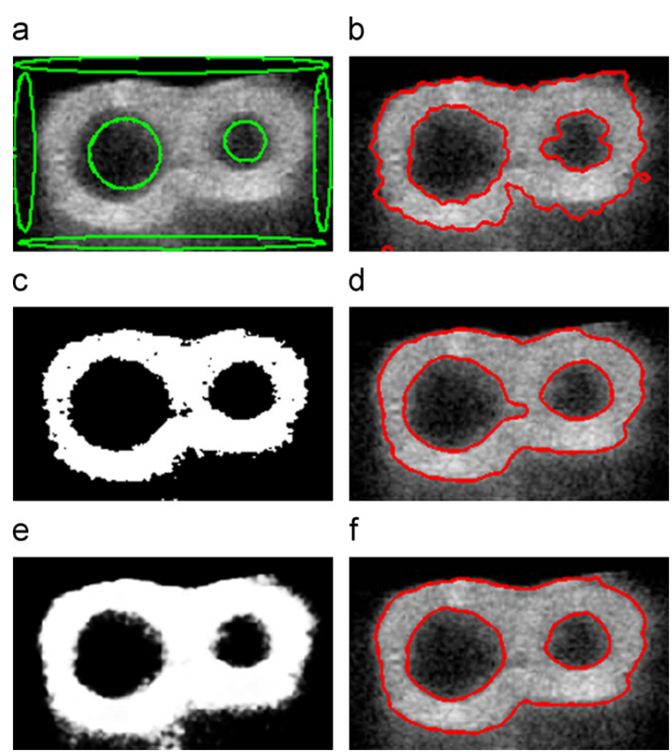

Fig. 1. Level set segmentation of the ultrasound carotid artery: (a) manual initialization; (b) final segmentation after 1800 iterations, with $\mu=0.1$, $\lambda=5$, $\nu=-1.5$, $\tau=2$; (c) initialization by thresholding (i: 120–250); (d) final segmentation after 100 iterations, with $\mu=0.1$, $\lambda=5$, $\nu=1.5$ and $\tau=2$; (e) initialization by spatial FCM; (f) final segmentation after 100 iterations, with $\mu=0.1$, $\lambda=5$, $\nu=1.5$ and $\tau=2$.

the performance comparison on the ultrasound image. Obviously, due to the weak boundaries and strong background noise, manual initialization did not lead to an optimal level set segmentation (Fig. 1a and b). On the contrary, both intensity thresholding (Fig. 1c and d) and fuzzy clustering (Fig. 1e and f) attracted the dynamic curve quickly to the boundaries of interest. It is noteworthy that an image inhomogeneity resulted in boundary leakage in Fig. 1d. In contrast, the proposed FCM segmentation with spatial restrictions remedied it substantially (Fig. 1f).

Fig. 2 illustrates the case of liver tissue and tumor segmentation from the CT scan by the fast level set evolution. There are two regions of cancerous tissue near the organ boundary. Segmentation is difficult because of the weak and irregular boundaries. The liver tissue itself is inhomogeneous, due to blood vessels. Again, it is challenging to determine an optimal initialization and the corresponding level set parameters. The results in Fig. 2 show that an FCM clustering has the best performance in terms of level set initialization. However, without the appropriate controlling parameters, level set segmentation could be either insufficient (Fig. 2f and h) or excessive (Fig. 2j and l).

Fig. 3 illustrates the more difficult case, which requires the separation of white matter (WM) and gray matter (GM) from an MRI slice of cerebral tissue. It is obvious that WM and GM intertwine with each other and are dispersed over the entire slice, which makes manual initialization nearly impractical (Fig. 3a and g). Both intensity thresholding (Fig. 3c and i) and fuzzy clustering (Fig. 3e and k) are advantageous in this regard. However, it is difficult to obtain a set of optimal parameters to control the level set evolution. As shown above, without the appropriate configuration, level set segmentation is even worse than the initial fuzzy clustering (Fig. 3d and j, f and l).

The objective of the second experiment was to evaluate the new fuzzy level set algorithm. The improvements are used to incorporate fuzzy clustering into level set segmentation for an automatic parameter configuration. Fig. 4 illustrates its performance on the ultrasound image of carotid artery. For those parameters that expand the level set contours (Fig. 4a), the initial FCM segmentation was truncated by a threshold of 0.99. In contrast, the threshold was 0.5 for the shrinking parameters (Fig. 4b). With the initial segmentation obtained by the spatial FCM, the level set evolution is not as sensitive to the controlling parameters and remains near the genuine boundary.

The proposed algorithm seems trivial in medical images with comparatively clear boundaries. However, in images without distinct boundaries (Figs. 5 and 6), it would be very important to control the motion of the level set contours. The operator has to monitor level set evolution continuously and adjust various controlling parameters frequently; otherwise inappropriate segmentation would come into being. In contrast, the new fuzzy level set algorithm is able to find out the controlling parameters from fuzzy clustering automatically. In particular, its solutions are robust and nearly optimal in all cases (Figs. 5c and f, 6c and f).

In summary, our proposed fuzzy level set algorithm allows flexible initialization for medical image segmentation. Three initializing paradigms were evaluated and compared in this paper (Figs. 1, 2 and 3). Manual demarcation and intensity thresholding

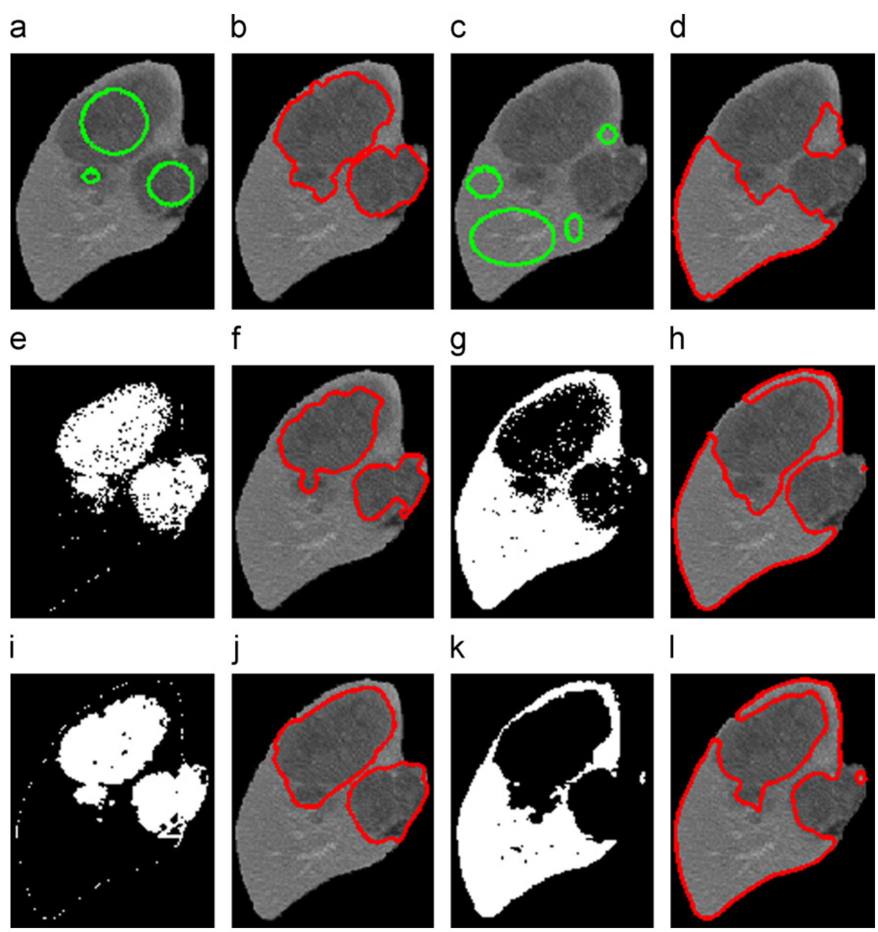

Fig. 2. Level set segmentation of CT liver tissues: (a) and (c) manual initialization; (b) and (d) final segmentation after 500 iterations, with $\mu=0.1$, $\lambda=5$, $\nu=-1.5$, $\tau=2$; (e) and (g) initialization by thresholding (e: 50–95; g: 95–250); (f) and (h) final segmentation after 100 iterations, with $\mu=0.1$, $\lambda=5$, $\nu=-1.5$, $\tau=2$; (i) and (k) initialization by spatial FCM; (j) and (l) final segmentation after 100 iterations, with $\mu=0.1$, $\lambda=5$, $\nu=1.5$ and $\tau=2$.

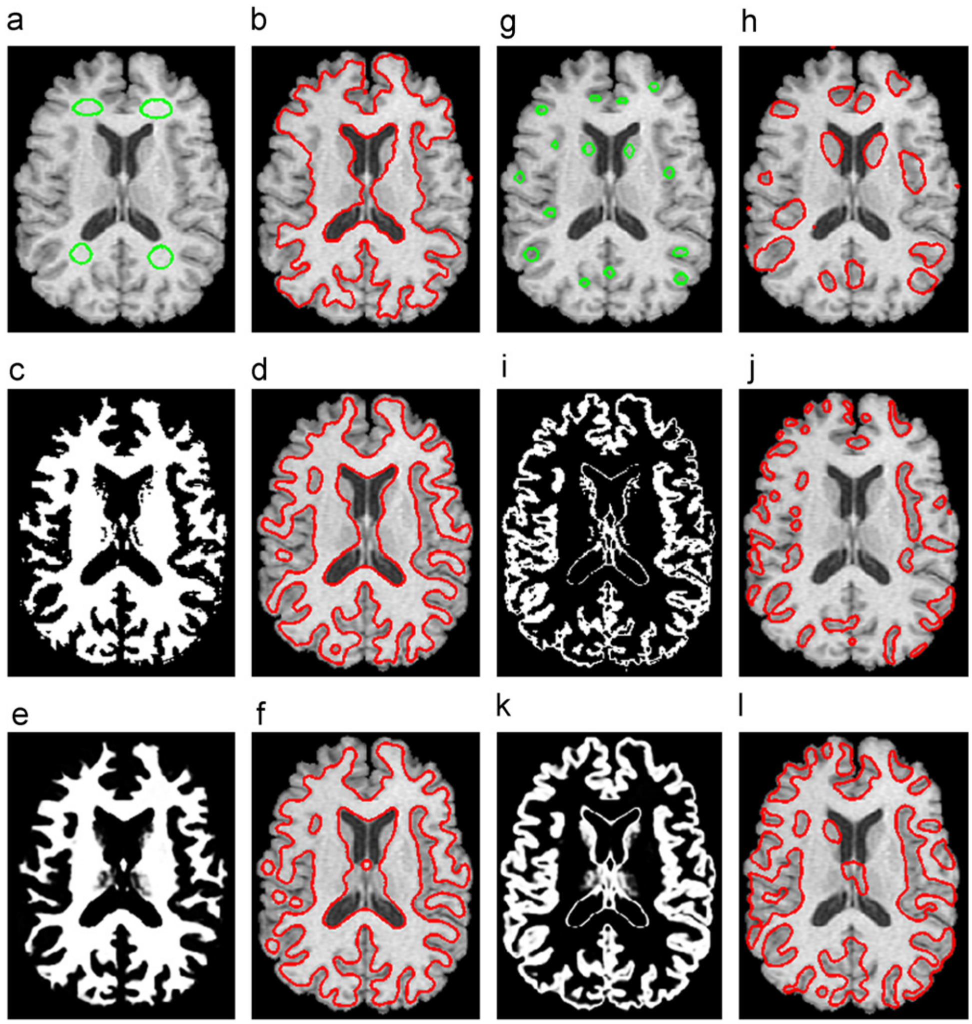

Fig. 3. Level set segmentation of MRI cerebral tissues (WM and GM): (a) and (g) manual initialization; (b) and (h) final segmentation after 2000 iterations, with $\mu=0.1$, $\lambda=5$, $v=-1.5$ and $\tau=2$; (c) and (i) initialization by thresholding (c: 170–250; i: 120—170); (d) and (j) final segmentation after 100 iterations, with $\mu=0.1$, $\lambda=5$, $v=1.5$ and $\tau=2$; (e) and (k) initialization by spatial FCM; (f) and (l) final segmentation after 100 iterations, with $\mu=0.1$, $\lambda=5$, $v=1.5$ and $\tau=2$.

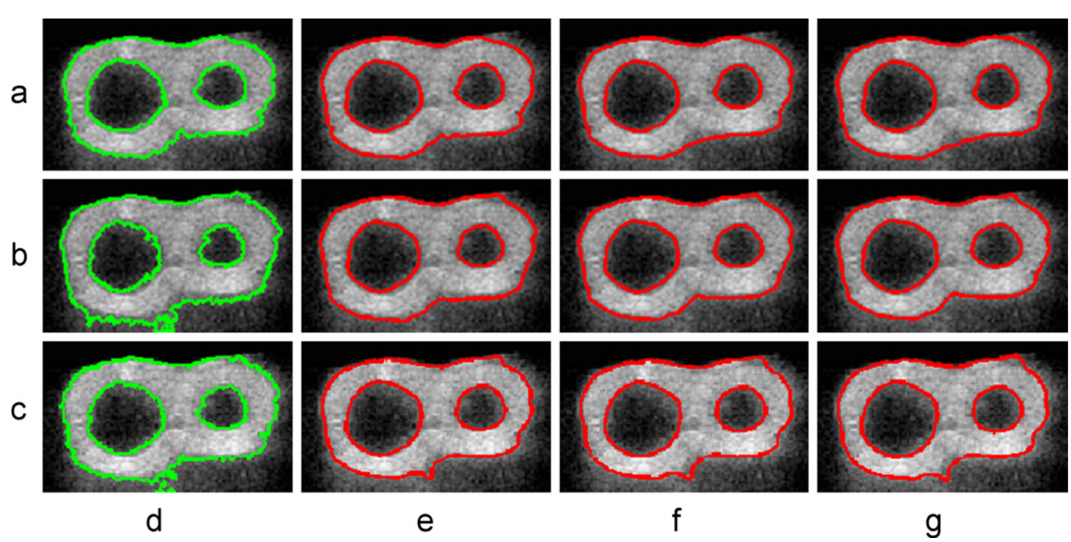

Fig. 4. Fuzzy level set segmentation of ultrasound carotid artery. Row (a) expanding FCM initialization, with $\mu=0.1$, $\lambda=2$, $v=-1$, $\tau=2$; row (b) shrinking FCM initialization, with $\mu=0.1$, $\lambda=2$, $v=1$ and $\tau=2$; row (c) level set segmentation, with the parameters from an FCM $\mu=0.067$, $\lambda=1.493$ and $\tau=2.987$, v is an FCM artery matrix; column (d) FCM initialization; column (e) after 100 iterations; column (f) after 200 iterations and column (g) after 300 iterations.

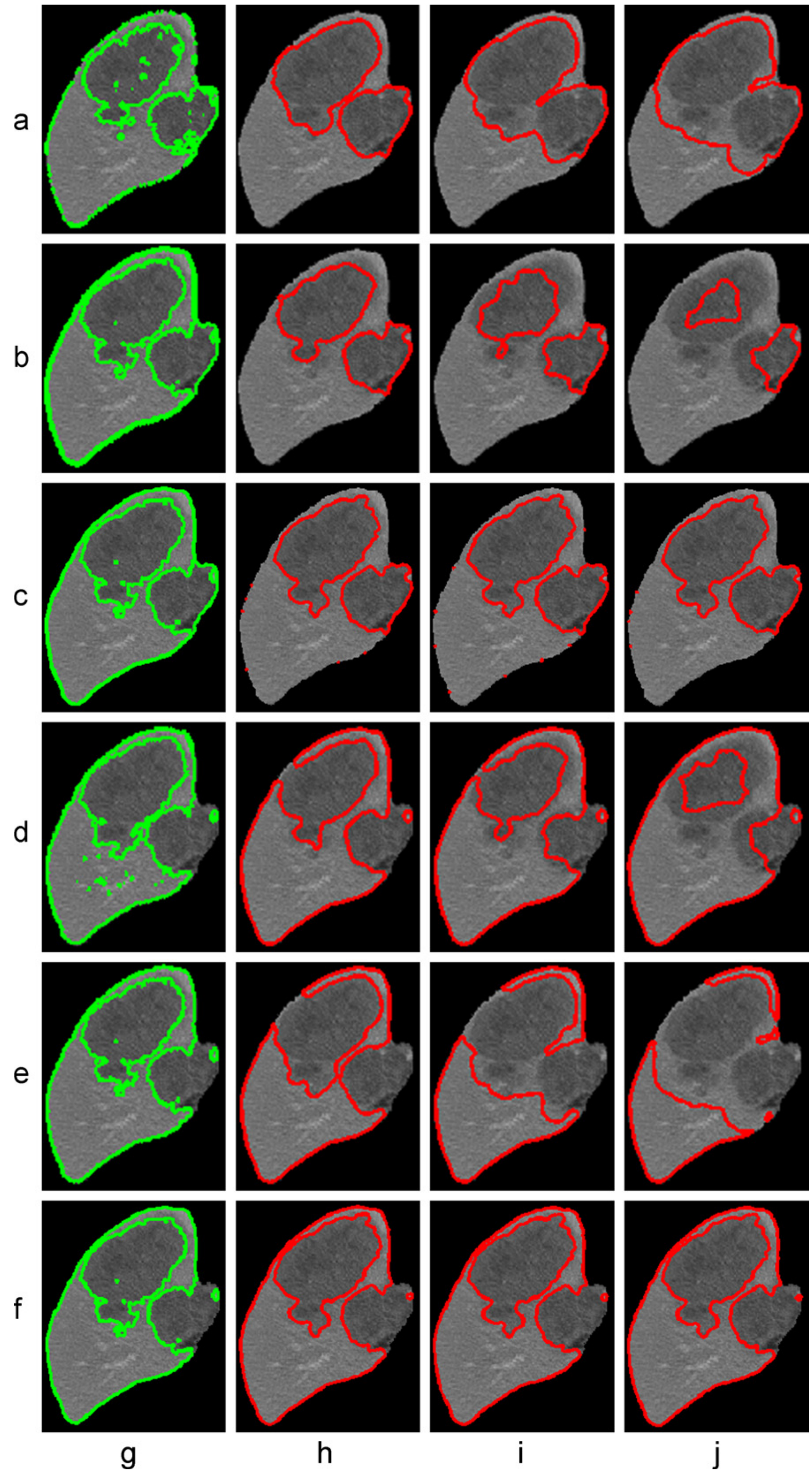

Fig. 5. Fuzzy level set segmentation of CT liver tissues: (a)–(c) tumor segmentation; (d)–(f) liver segmentation; (a) and (d) expanding FCM initialization, with $\mu=0.1$, $\lambda=2$, $\tau=2$ and $v=-1$; (b) and (e) shrinking FCM initialization, with $v=1$; (c) tumor segmentation, with the parameters from an FCM $\mu=0.102$, $\lambda=0.983$ and $\tau=1.965$, G is the enhanced balloon force; (f) liver segmentation, with the parameters from an FCM $\mu=0.079$, $\lambda=1.265$ and $\tau=2.531$, G is the enhanced balloon force; (g) FCM initialization; (h) after 100 iterations; (i) after 200 iterations and (j) after 300 iterations.

are convenient for level set initialization. Actually most level set systems in the literature adopt this form of initialization [7,23,24]. However, the boundaries between physiological tissues in medical images are generally weak and indistinct. With regards to image inhomogeneity and boundary leakage, manual initialization is obviously not a reliable choice for an optimal level set segmentation

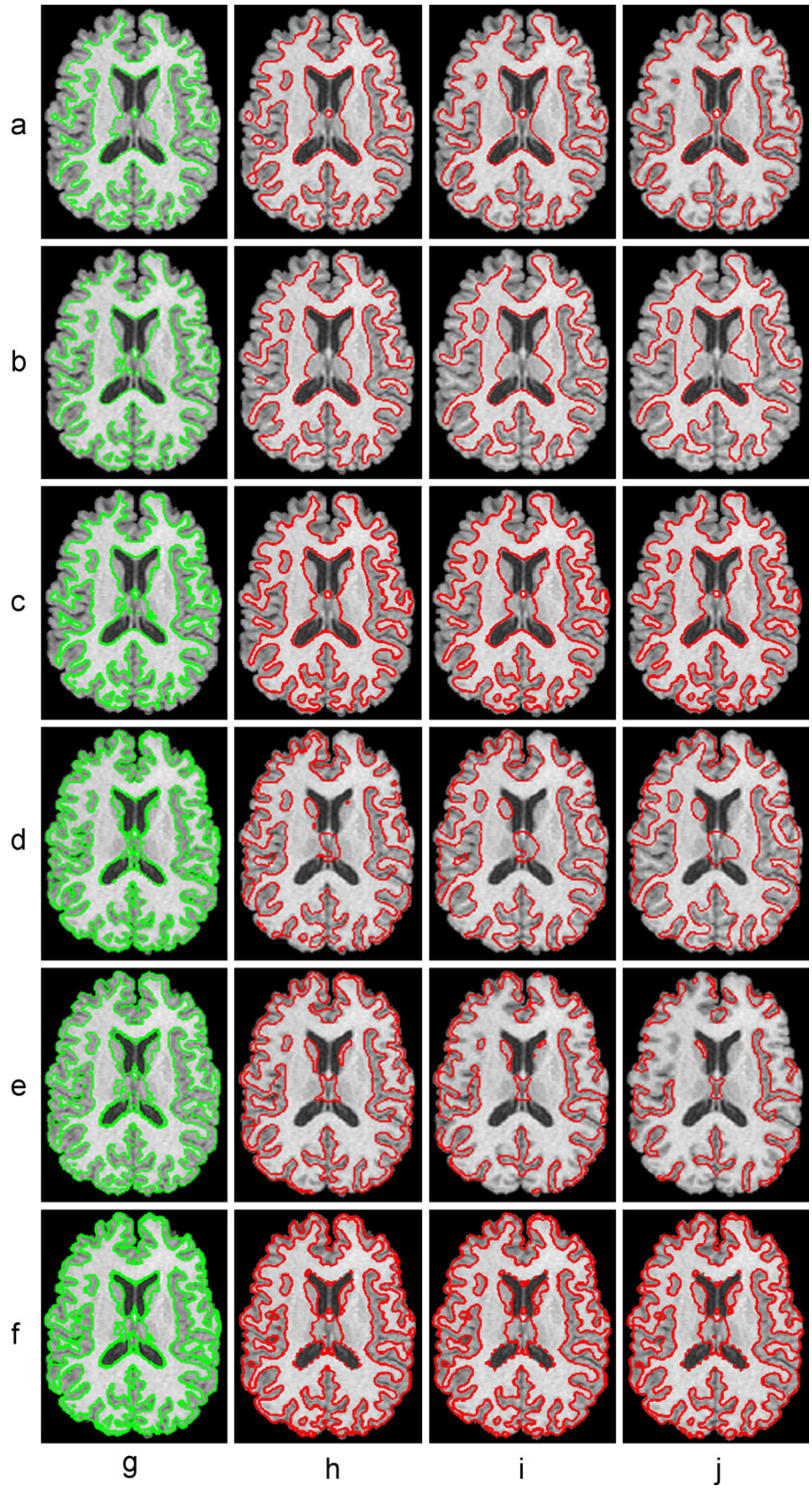

Fig. 6. Fuzzy level set segmentation of MRI cerebral tissues: (a)–(c) WM; (d)–(f) GM; (a) and (d) expanding initialization, with $\mu=0.1$, $\lambda=2$, $\tau=2$, $\nu=-1$; (b) and (e) shrinking initialization, with $\nu=1$; (c) WM segmentation, with the parameters from an FCM $\mu=0.162$, $\lambda=0.616$ and $\tau=1.231$, G is an FCM WM matrix; (f) GM segmentation, with parameters from an FCM $\mu=0.348$, $\lambda=0.287$ and $\tau=0.575$, G is an FCM GM matrix; (g) FCM initialization; (h) after 100 iterations; (i) after 200 iterations and (j) after 300 iterations.

(Figs. 1 and 2). Furthermore, the components of interest are often dispersed over the entire image. It is not convenient to demarcate them individually (Fig. 3). In contrast, intensity thresholding is advantageous in this regard. Nevertheless, it requires careful regularization for optimal thresholds, which is particularly challenging for those physiological tissues that intertwine with each other (Fig. 3).

Fuzzy clustering is able to adaptively obtain the approximate boundaries of potential components of interest, and is thus suitable to initiate an image segmentation. However, the standard FCM algorithms, which are concerned with an intensity information only, are not robust enough for medical image segmentation, due to noise and artifacts. The enhanced spatial FCM attempts to unify intensity and spatial information as a whole. This algorithm of spatial fuzzy clustering has been shown less susceptible to different types of noises; hence, it is suitable to initiate level set evolution for medical image segmentation.

Level set evolution is subject to various forces from the active curve itself (the internal terms) and the image under investigation (the external terms). It is difficult to coordinate these forces for an optimal image segmentation. Optimal parameters can be achieved only by trial and error for the specific images. Figs. 4–6 show that, despite good initialization, the inappropriate controlling parameters may lead to an inferior segmentation. Moreover the operator has to be alert to level set evolution in the cases of medical images with weak or ambiguous boundaries, otherwise insufficient or excessive segmentation will occur eventually. The new fuzzy level set algorithm is advantageous, because the implicit interface stabilizes once it approaches the genuine boundaries. In addition, it is possible to estimate the nearly optimal controlling parameters from the results of spatial fuzzy clustering automatically. All of them facilitate the level set segmentation in practice.

It is appropriate to refer the work presented in this paper to those incorporating prior knowledge into deformable models [10,11,13,21]. Unfortunately, it is not an easy task to obtain reliable prior knowledge and models in medical image analysis [14]. For example, computerized liver tumors segmentation is complicated, in that both the shape and the intensity of liver tumors vary from modality to modality, from person to person, and even at the different pathological stages. Fuzzy clustering is able to obtain the potential components of interest adaptively. It therefore serves as an effective source of prior knowledge for level set segmentation.

6. Conclusion

A new fuzzy level set algorithm has been proposed for automated medical image segmentation. It utilizes fuzzy clustering as the initial level set function. The enhanced FCM algorithms with spatial information can approximate the boundaries of interest well. Therefore, level set evolution will start from a region close to the genuine boundaries. In addition, the new algorithm estimates the controlling parameters from fuzzy clustering automatically. This has reduced manual intervention. Finally, the level set equation is modified with variable balloon forces, so that the level set evolution could be regularized locally by means of spatial fuzzy clustering. In other words, the level set evolution stabilizes automatically once it approaches the genuine boundaries, which not only suppresses boundary leakage, but also alleviates manual intervention. All these improvements lead to a robust algorithm for medical image segmentation. Performance evaluation has been carried out with different types of medical images. The results were confirmed promising.

The fuzzy level set method presented in this paper is derived from the classical Hamilton-Jacobi functional [16,17], where the level set evolution is subject to various internal and external forces. It is possible to consider medical image segmentation as a Mumford–Shah problem, where the level set functions are formulated to minimize an energy function for an optimal segmentation [2,7,10,21]. The latter methods are not as sensitive to the initial contours as the former ones. In the following research, it is interesting to utilize the approaches proposed in this paper to the Mumford–Shah level set methods, for medical image segmentation.

Conflict of interest statement

None declared.

Acknowledgment

This work was partially supported by the National University of Singapore, Singapore (JSPS—Singapore Research Project Grant nos.: R-265-000-285-112 and R-265-000-285-646). The authors would like to thank Dr. Li Chunming (Institute of Imaging Science, Vanderbilt University, Nashville, USA) for his code of fast level sets and some of the medical images in this paper.

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