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Local Binary Fitting Segmentation by Cooperative Quantum Particle Optimization

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Abstract

Recently, sophisticated segmentation techniques, such as level set method, which using valid numerical calculation methods to process the evolution of the curve by solving linear or nonlinear elliptic equations to divide the image availably, has become being more popular and effective. In Local Binary Fitting (LBF) algorithm, a simple contour is initialized in an image and then the steepest-descent algorithm is employed to constrain it to minimize the fitting energy functional. Hence, the initial position of the contour is difficult or impossible to be well chosen for the final performance. To overcoming this drawback, this work treats the energy fitting problem as a meta-heuristic optimization algorithm and imports a varietal particle swarm optimization (PSO) method into the inner optimization process. The experimental results of segmentations on medical images show that the proposed method is not only effective to both simple and complex medical images with adequate stochastic effects, but also shows the accuracy and high efficiency.

Keywords: *local binary fitting; segmentation; particle swarm optimization; Lévy flights; active contour*

1. Introduction

Image segmentation plays an important part of image processing, and is also the premise and basis of image analysis and image understanding and recognition. The classic image segmentation method based on two fundamental properties of pixels: discontinuity and similarity. Some sophisticated segmentation techniques, such as Level Set method in PDF [1-3], which using valid numerical calculation methods to process the evolution of the curve by solving linear or nonlinear elliptic equations to divide the image availably. Especially, some level set methods, such as LBF method [4], are sensitive to size of the local image contours, shapes, and initial positions. In addition, the most current level set models are usually non-convex energy functional; whose solutions are the local minima rather than global ones. So it is difficult to achieve the desired segmentation results, but also affects the effectiveness of the algorithm.

The image segmentation algorithm based on level set is essentially an optimization problem, which minimizing the energy functional. Hence, the variational level set model of energy functional minimization problem could be formalized into meta-heuristic optimization problem, and by using the particle swarm optimization method and level set competitive image segmentation method. Then the particle swarm optimization method could be used to segment the image with the competition of level set method [5].

However, the current study shows that the particle swarm optimization has not been deeply embedded in the level set method as an organic integrity. It is possible to use PSO to replace some unnecessary convolution operations and take the advantages of strong searching capability and fast convergence speed. Moreover, most research also not combine the regularization model into it and promote the global performance. On the other side, the image segmentation algorithm based on level set is essentially an optimization problem, which minimizing the energy functional. Hence, the variational level set model of energy functional minimization problem could be formalized into meta-heuristic optimization problem, and by using the particle swarm optimization method and level set competitive image segmentation

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method. Then the particle swarm optimization method could be used to segment the image with the competition of level set method. In this article, we embed the particle swarm optimization into the LBF model and algorithm to implement the inner optimization operation and test it on the medical image segmentation.

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2. Model Review

2.1. Review of Level Set Method

As the computer image has high real-time and dynamic features and randomness of topology, the level set method is used to solve the contour variation of processing of image. Essentially, the level set method is an approach to solve curve evolution using implicit method to denote the closed curve in a plane. It represents the evolved curve to a partial differential equation (PDF) of the zero level set function, avoiding the trace to the evolution process and relevant parameterization. The basic idea of level set is to embed the evolved curve as a zero level set function to a higher dimension function, then to get the evolution equation from the one of closed hyper-surface. Because the embedded closed curve is always be kept as a set of points on the a zero level set cutting plane, so only the position of this set of points is needed to compute the evolution result. Figure 1 shows a landscape of a zero level set function, i.e., the square curve, and its cutting plane. In general, a combination of normal, vector field-based and curvature-based forces is often used to evolve the curve to shrink under it in the normal direction.

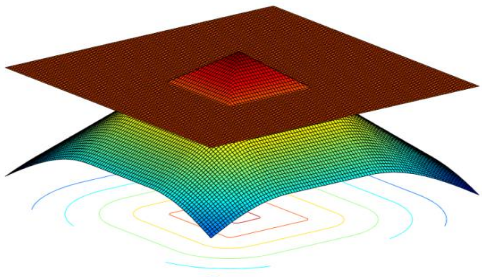


Figure 1. Landscape of Level Set and Cutting Plane

2.2. Formalization of LBF Model

As a successor of level set model, the LBF model was recently applied into the image segmentation with intensity inhomogeneity using the local intensity value. In this paper, we define the problem in only two regions, i.e., the 2 dimension. Given an image$I: \Omega \subset R^2$, x is the vector related to the image pixel, where y is the one of neighborhood of x. The basic the energy functional can be defined as follows:

$$\varepsilon^{LBF}(C, f_1, f_2) = \lambda_1 \int_\Omega \left[\int_{out(C)} K_\sigma(x-y)|I(y) - f_1(x)|^2 H(\phi(x))dy\right] dx + \lambda_2 \int_\Omega \left[\int_{in(C)} K_\sigma(x-y)|I(y) - f_2(x)|^2 1 - H(\phi(x))dy\right] dx \quad (1)$$

where λ_1 and λ_2 are weight coefficients, $f_1(\cdot)$ and $f_2(\cdot)$ are the fitting functions denote the approximation about the gradation of image of $in(C)$ and $out(C)$ respectively. $K_\sigma(\cdot)$ is a Gaussian kernel with standard deviation of σ.

Furthermore, the energy functional could be represented by a level set formulation in the below format:

$$\varepsilon^{LBF}(C,f_1,f_2)=\lambda_1\int_{\Omega}\left[\iint_{out(C)}K_\sigma(x-y)|I(y)-f_1(x)|^2H(\phi(x))dy\right]dx$$
$$+\lambda_2\int_{\Omega}\left[\int_{in(C)}K_\sigma(x-y)|I(y)-f_2(x)|^2 1-H(\phi(x))dy\right]dx \quad (2)$$

To guarantee the smoothness of the contour curve C and the level set function, an arc length rule term $L(\phi)$ and a penalty term $P(\phi)$ are imported in the energy functional. Hence, the final definition of the energy functional $E^{LBF}(C,f_1,f_2)$ can be written in the form:

$$E^{LBF}(C,f_1,f_2)=\varepsilon^{LBF}(C,f_1,f_2)+\mu P(\phi)+\nu L(\phi) \quad (3)$$

Then, the minimization problem could be converted to solving a level set evolution equation. Concretely, in the level sec model, the contour curve $C\subset\Omega$ can be represented by the zero level set of a Lipschitz function $\phi\colon\Omega\subset R^2$. In order to minimize the energy functional $E^{LBF}(C,f_1,f_2)$ with respect to $\phi(\cdot)$, we use the below gradient decent flow:

$$\frac{\partial\phi}{\partial t}=-\delta_\epsilon(\phi)(\lambda_1e_1-\lambda_2e_2) \quad (4)$$

Subsequently, the complete curve evolution equation is as follows:

$$\frac{\partial\phi}{\partial t}=\mu\left(\Delta\phi-div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right)+\nu\delta_\epsilon(\phi)div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)-\delta_\epsilon(\phi)(\lambda_1e_1-\lambda_2e_2) \quad (5)$$

where the coefficients λ_1 and λ_2 weight the two integral over regions inside/outside the contour. $e_1(\cdot)$ and $e_2(\cdot)$ are defined as follows:

$$e_1(x)=\int_\Omega K_\sigma(x-y)|I(y)-f_1(x)|^2dy \quad (7)$$

$$e_2(x)=\int_\Omega K_\sigma(x-y)|I(y)-f_2(x)|^2dy \quad (8)$$

In general, Heaviside function H is approximated by a smooth function H_ϵ which is defined by the following formula:

$$H(x)=\begin{cases}1, & if\ x\geq 0\\ 0, & if<0\end{cases} \quad (9)$$

$$H_\epsilon(x)=\frac{1}{2}\left[1+\frac{2}{\pi}\arctan\left(\frac{x}{\epsilon}\right)\right] \quad (10)$$

The fitting functions $f_1(x)$ and $f_2(x)$ will be updated according to the following equation:

$$f_1(x)=\frac{K_\sigma(x)*[H_\epsilon(\phi)I(x)]}{K_\sigma(x)*H_\epsilon(\phi)} \quad (11)$$

$$f_2(x)=\frac{K_\sigma(x)*[1-H_\epsilon(\phi)I(x)]}{K_\sigma(x)*[1-H_\epsilon(\phi)]} \quad (12)$$

2.3. LBF Algorithm

The main procedure of LBF can be summarized as following Algo. 1. Firstly, the initial level set function ϕ^0 is simply defined as a binary function:

$$\phi^0(x)=\begin{cases}-c_0, & if\ x\in \mathrm{R}^2;\\ c_0, & else;\end{cases} \quad (13)$$

Algorithm 1. The pseudo-code of LBF
Initialization:

Read the input image $I: \Omega \subset \mathrm{R}^2$.
Build the initial level set function ϕ^0.
Initialize the iteration number $n = 0$.
Scale parameter in Gaussian kernel.

Repeat:

Compute Heaviside function according to Eq. (9);
Compute Dirac function according to Eq. (12);
Compute e_i according to Eq. (6) and (7);
Upate the value of $f_1(x)$ and $f_2(x)$ using (10) and (11);
Upate the level set function as ϕ^{n+1} according to Eq. (5);

Until $|\phi^{n+1} - \phi^n| < TH$;
Output the segmentation result $\phi = \phi^{n+1}$.

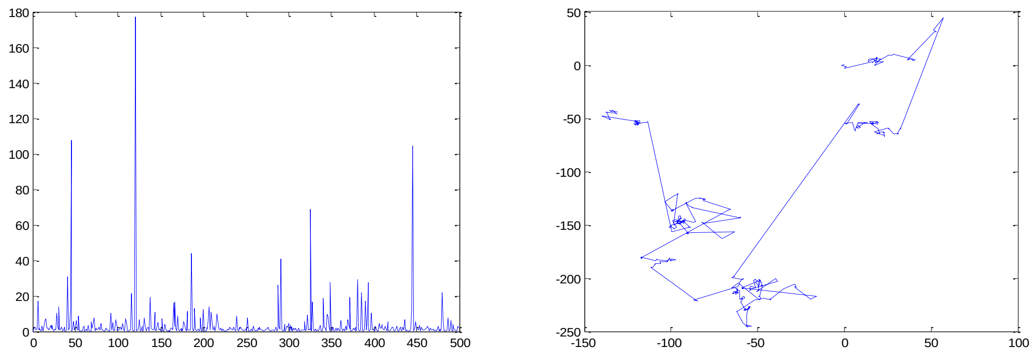
3. Particle Swarm Optimization (CQPSO-LF) CQPSO-LF aided LBF Algorithm
3.1. CQPSO-LF Algorithm

Lévy flights [6], named after the French mathematician Paul Pierre Lévy, are Markov processes. After a large number of steps, the distance from the origin of the random walk tends to a stable distribution. Lévy flights, which can be characterized by an inverse square distribution of step length, may optimize the random search process when targets are scarce and scarcity of resources. In contrast, Brownian motion is usually suit for the case when need to locate abundant prey or targets. These traits of two random walks inspired us to improve our swarm intelligence optimization, where Lévy flights can improve the ability of "exploration" while Brownian motion benefits the "exploitation".

Mathematically, Lévy flights are a kind of random walk whose step lengths meet a heavy-tailed Lévy alpha-stable distribution, often in terms of a power-law formula, $L(s) \sim |s|^{-1-\beta}$, where 0<β≤2 is an index. A typical version of Lévy distribution can be defined as [7].

As the change of β, this can evolve into one of Lévy distribution, normal distribution and Cauchy distribution. The increments of Lévy flights are distributed according to a heavy-tailed probability distribution. Figure 2 shows an example of this kind of distribution.

$$L(s,\gamma,\mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} exp[-\frac{\gamma}{2(s-\mu)}] \frac{1}{(s-\mu)^{3/2}}, \\ \qquad 0 < \mu < s < \infty; \\ 0, s \le 0. \end{cases} \tag{12}$$



(a) (b)

Figure 2. An Instance of 2D Lévy Flights in 500 Steps

Taking the 2D-Lévy flights for instance, the step lengths and distance 00 steps of random walks obeying a Lévy distribution are shown as in Figure 2(a) and Figure 2 (b) respectively. Note that the Lévy flights are often efficient in exploring unknown and large-scale search space than Brownian walks. One reason for this argument is that the variance of Lévy flights $\delta^2(t) \sim t^{3-\beta}, 1 \leq \beta \leq 2$ increases faster than that of Brownian random walks, i.e., $\delta^2(t) \sim t$. Also, compared to Gaussian distribution, Lévy distribution is advantageous since the probability of returning to a previously visited site is smaller than for a Gaussian distribution, irrespective of the value of μ chosen.

From the update strategy of CQPSO-LF in our previous work [8,9] , we can draw a conclusion that all particles in CQPSO-LF will converge to a common point, leaving the diversity of the population extremely low and particles stagnated without further search before the iterations is over. To overcome the problem, we exert a disturbance generated by Lévy flights on the mean best position, global best position and electoral best position when the swarm is evolving as shown in the following Eq.(14)-Eq.(16). To the local attractor, the hop steps in Lévy flights promise the random traversal in the search space. However, to the global and electoral best location, they only need a slightly disturbance, i.e., the angles meet a uniform distribution, to exploit the particles nearby.

$$C_d' = C_d + \varepsilon_3 \times Step_{Levy} \tag{14}$$

$$P_{gd}^{best\prime} = P_{gd}^{best} + \varepsilon_1 \times Angle_{Levy} \tag{15}$$

$$P_{cgd}^{best\prime} = P_{cgd}^{best} + \varepsilon_2 \times Angle_{Levy} \tag{16}$$

where ε_1, ε_2 , ε_3 is a pre-specified parameter, $\mathrm{Step_{Levy}}$ is a number in a sequence by Lévy flights, angle is the angles of directions in Lévy flights.

Differently with other similar methods, we use the output parameters of Lévy flights to intervene the position change directly, which can be seen in the Eq.(17) as follow, where $\mathrm{Angle_{Levy}}$ and $\mathrm{Step_{Levy}}$ are the output parameters of Lévy flights which are random generated, while ε_1, ε_2, ε_3 are the parametric empirical coefficient.

$$P_{id}^{t+1} = \varphi \times P_{id}^{best} + \psi \times \left(P_{gd}^{best} + \varepsilon_1 \times Angle_{Levy}\right) + (1 - \varphi - \psi) \times (P_{cgd}^{best} + \varepsilon_2 \times Angle_{Levy}) \pm \beta \times \left|(C_d + \varepsilon_3 \times Step_{Levy}) - P_{id}^{t}\right| \times ln(1/u) \tag{17}$$

3.2. CQPSO-LF Aided LBF Algorithm (LBF-CQPSO-LF)

The original LBF algorithm is a deterministic algorithm that is also sensitive to size of the local image contours, shapes, and initial positions. At first, a simple contour is initialized in an image and then the steepest-descent algorithm is employed to constrain it to minimize the fitting energy functional. So the initial position of the contour is difficult or impossible to well choice for the final performance. In light of this shortcoming, we propose a new hybrid model in this article to utilize a population based swarm intelligence algorithm to select the good candidate contours with the global minimum of the fitting energy functional. Meanwhile, the level set method is also used to evolve the candidate contours and also get the cost function. During the iterations, the initial seeds are elected by the CQPSO-LF algorithm to achieve the best performance segmenta- -tion of the image. The whole framework of the CQPSO-LF aided LBF Algorithm (LBF-CQPSO-LF) is described in the Algorithm 2.

Algorithm 2. The pseudo-code of LBF-CQPSO-LF
Initialization:
Read the input image $I: \Omega \subset \mathrm{R}^2$.
Build the initial level set function ϕ^0.
Initialize the iteration number $n = 0$.
Scale parameter in Gaussian kernel.
While iteration <TH
For k=1 to N
Compute Heaviside function;
Compute Dirac function;
Compute e_i;
Upate the value of $f_1(x)$ and $f_2(x)$;
Upate the level set function as ϕ^{n+1};

Until $|\phi^{n+1} - \phi^n| < TH$;
Output the segmentation result $\phi = \phi^{n+1}$.
End For
For k=1 to N
SubSwarm Evaluation: Evaluate the fitness values $E^{LBF}(C, f_1, f_2)$ of particles in sub-swarms according to the fitness function, and get C_d, P_{id}^{best}, and P_{gd}^{best}.
SubSwarm Disturbance: Obtain the values $P_{gd}^{best\prime}$, C_d', by Lévy flights disturbance.
Overall Evaluation: Elect the compositional global best position P_{cgd}^{best}.
Overall Disturbance: Obtain the $P_{cgd}^{best\prime}$ by Lévy flights disturbance.
Update Position: Renovate the positions of particles P_{id}^{t+1}.
End For
End While

4. Experimental Results and Analysis

In this section, some typical numerical examples are executed and shown to validate the effectiveness of the proposed method for medical images segmentation. All the experiments are conducted in Matlab R2014b(64 bit), on a workstation platform of PC with an Intel(R) Xeon(R) CPU E3-1230 V2 @ 3.30GHz Duo Core, 8.00GB RAM under a OS of Windows 7(64 bit) Ultimate Service Pack 1.

The aim of the experiments is to evaluate the effectiveness of LBF-CQPSO-LF method. At first, we choose one simple blood vessel image to test the validity of the method. The 3D landscape of the blood vessel image is shown in Figure 3. In this experiment, we use the kernel function to help define the local binary fitting energy, whose shape can be found in Figure 4. As shown in Figure 5(a-d), the method could not only segment out the desired objects increasingly, but also is stable to initial contours.

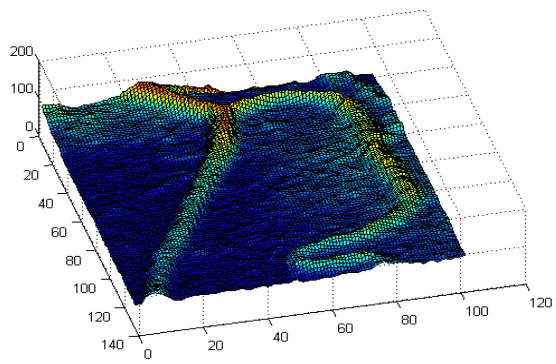


Figure 3. 3D Landscape of the Blood Vessel Image

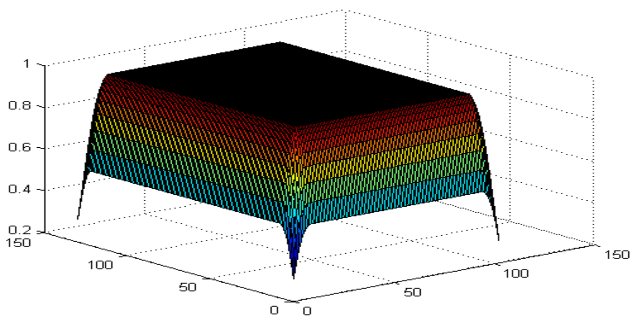


Figure 4. Shape of Kernel Function

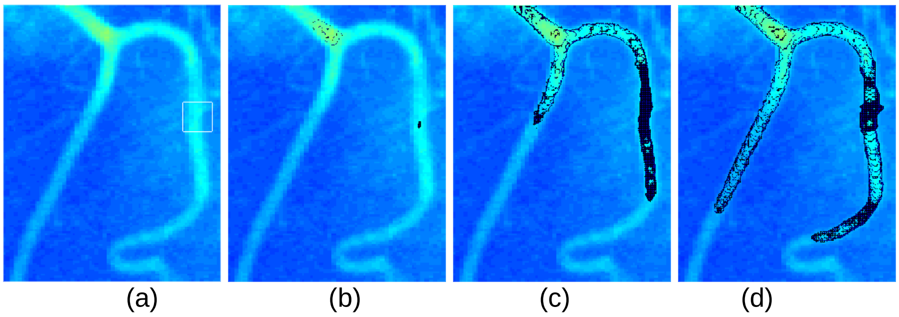


Figure 5. Iterations of Segmentation of Blood Vessel Image

In the sequent experiment, we utilized the LBF-CQPSO-LF in the real application scenario, i.e., an endocrine system medical image. To show the details explicitly, we transformed the image into pseudo-color in the view of Matlab. The initial contour and ones in the iterations are as shown in Figure 6(a). The initial rectangular region is fixed in the center of the image, which is not sensitive to the final result any more. Due to the stochastic characteristic of this algorithm, some targets with weak boundaries could be well identified at Figure 6(b-d).

The final segmentation results of endocrine system medical image after post-processing can be found in Figure 7(a,b). Totally, the proposed algorithm can avoid the trapping in the local minima when the energy functional evolves. Moreover, as the import of the Lévy Flights, the noise disturbance is greatly reduced. Especially, after removing trivial edges, the refined segmentation can be seen in the Figure 7(b) with the integrated and clean topological structures, which could be the input of the further analysis.

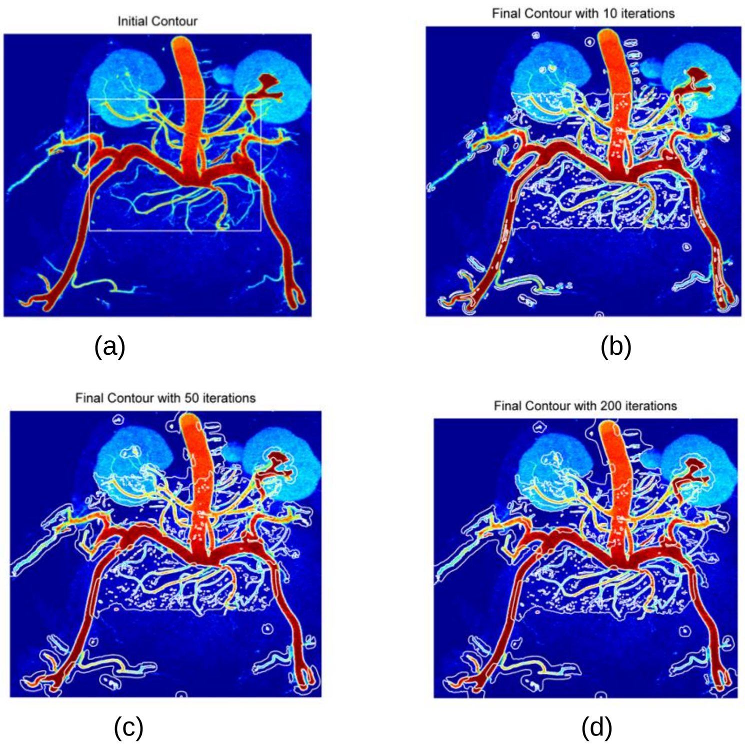
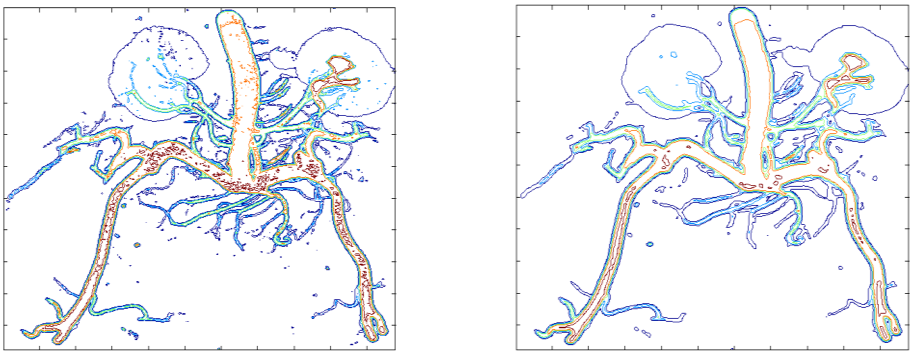


Figure 6. Final Segmentation Results of Endocrine System Medical Image



(a) (b)

Figure 7. Shape of Kernel Function

To evaluate the performance of proposed algorithm, LBF-CQPSO-LF, we adopted an index called Segmentation Performance Measure (SPM) imported in literature [10] as an benchmark, where the Automatically Segmented Image (ASI) is used to compare with the Manually Segmented Image (MSI) to calculate the similarity by the Equation (18). Table 1 presents the quantitative segmentation performance of blood vessel and endocrine system sample images by SPM and running time. It can be seen that the proposed algorithm could reach high SPM, i.e., achieve desired initialization insensitive segmentation performance for both simple and complex medical images.

$$SPM = \frac{2 * (ASI \cap MSI)}{|ASI| + |MSI|} \quad (18)$$

Table 1. The Performance of LBF-CQPSO-LF

Test Run	Iterations No.	SPM (%)		Time taken (s)	
		Blood Vessel	Endocrine System	Blood Vessel	Endocrine System
1	250	99.2579	97.3581	186.51	347.26
2	200	99.1547	98.156	157.03	291.08
3	300	99.3768	98.8245	201.65	414.73
4	150	98.6287	97.0689	86.49	156.4

7. Conclusion

In this article, a novel level set model aided by PSO was proposed to solve automated medical image segmentation. The experimental result of segmentations on medical images shows that the proposed method is not only effective to both simple and complex images with adequate stochastic effects, but also shows the accuracy and high efficiency. However, our methodstill has some limitations. For example, as our method stochastic algorithm naturally, so it is hard to control the speed of convergence and stability. As our future studies, we will investigate how to expand this method to the three-dimension case and consider multi-phase level sets circumstance. Moreover, as the limitation of slow convergence, we aim to promote the rate of convergence according to some approximate methods.

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