An Optimized Level Set Method Based on QPSO and Fuzzy Clustering

Ling YANG††, Member, Yuanqi FU†, Zhongke WANG††, Xiaojiong ZHEN†, Zhipeng YANG†, and Xingang FAN†††∗∗, Nonmembers

SUMMARY A new fuzzy level set method (FLSM) based on the global search capability of quantum particle swarm optimization (QPSO) is proposed to improve the stability and precision of image segmentation, and reduce the sensitivity of initialization. The new combination of QPSO-FLSM algorithm iteratively optimizes initial contours using the QPSO method and fuzzy c-means clustering, and then utilizes level set method (LSM) to segment images. The new algorithm exploits the global search capability of QPSO to obtain a stable cluster center and a pre-segmentation contour closer to the region of interest during the iteration. In the implementation of the new method in segmenting liver tumors, brain tissues, and lighting images, the fitness function of the objective function of QPSO-FLSM algorithm is optimized by 10% in comparison to the original FLSM algorithm. The achieved initial contours from the QPSO-FLSM algorithm are also more stable than that from the FLSM. The QPSO-FLSM resulted in improved final image segmentation.

key words: image segmentation, fuzzy c-means clustering method (FCM), level set method (LSM), quantum particle swarm optimization (QPSO), QPSO-FLSM method

1. Introduction

Computerized image segmentation, which automates or facilitates the delineation of anatomical structures and other regions of interest, plays a crucial role in many medical-imaging applications [1]. However, it remains a challenging problem due especially to poor resolutions and weak contrasts in the raw images [2]. Among the methods that have been developed for medical image segmentation, level set method (LSM) has been widely used [3]–[6] attributable to its advantages. First, the numerical computations of LSM that involve curves and surfaces can be performed on a fixed Cartesian grid. Second, LSM is able to represent contours with complex topological features [7]. However, the LSM is sensitive to the cluster center initialization.

Aiming at the sensitivity problem of the LSM to the initial contour, Li et al. proposed a LSM algorithm that is based on spatial fuzzy c-means (FCM) [8]–[10] clustering method, which improves the cluster center initialization [2]. The FCM automatically pre-segments images for the subsequent LSM segmentation. This FCM-based LSM (FLSM) algorithm improves the segmentation effect and avoids manual intervention for such as manually setting the initial contour. The FCM is a local search algorithm, which improves local-region pre-segmentation and the final segmentation result [11]. Due to the nature of the FCM, it finds only a local optimal solution of the objective function and is sensitive to initial contour and control parameters, especially in more complex images. This limitation leads to the high sensitivity of the pre-segmentation to the initial contour, and consequently, an unstable segmentation.

In this study, we adopted the quantum particle swarm optimization (QPSO) [12]–[14], which provides the capability of achieving rapid global convergence and maximum optimization, to improve the FCM pre-segmentation and ultimately the LSM segmentation. In implementation of QPSO, the first-generation particles, which represent the solution to each optimization problem, are generated randomly. The QPSO algorithm improves the segmentation effect and avoids manual intervention for such as manually setting the initial contour. The FCM is then used to initialize the cluster centers of the first-generation particles. Finally, QPSO and FCM are performed alternatively and iteratively to acquire a set of globally stable cluster centers for the initial contour that is used in the level set segmentation. The segmentation results with the new combined QPSO-FLSM method show improved stability and precision of segmentation with less initialization sensitivity.

The remainder of this paper is organized as following. Section 2 describes the FLSM algorithm of level set method with fuzzy clustering. Section 3 elaborates on the QPSO algorithm. Section 4 presents in detail the new optimized level set segmentation method that is based on QPSO-FLSM. Section 5 reports the experiments and relevant discussions. Concluding remarks are drawn in Sect. 6.

2. Algorithm of Fuzzy Level Set Method (FLSM)

Level set method (LSM) is a widely used image segmentation method, in which hyper surfaces of any dimensions, such as curves or surfaces, can be represented by a zero-level set of feature points. The fuzzy level set method
(FLSM) [15], [16] is indeed a level set method but utilizes the automatic initial contour and parameter configuration from FCM. According to the concept of fuzzy partition in FCM, the fuzziness index is introduced into the objective function in FLSM. Each region of interest in the image corresponding to each cluster center is composed of a number of image pixels whose membership-degree value are within the extent of the cluster center. The initial categories can then be selected and the approximate initial contours are formed for all of the regions of interest, so that inadquate-evolution or over-segmentation can be avoided.

In FCM, all objects (of total number n) are assigned into c clusters (c ≤ n) based on their attributes. The cluster centers and the scope of each cluster (i.e., category) are estimated adaptively in order to minimize a pre-defined cost function. For image segmentation, its feature space (e.g., the gray level of pixels) is represented by

\[ X = (x_1, x_2, \ldots, x_n), \]

where \( x_j \) represents the j-th feature point, \( n \) equals the number of image pixels \( N_X \times N_Y \) \( (N_X \text{ and } N_Y \text{ are dimensions of the image in pixels}) \). For the given number of possible target clusters \( 2 \leq c \leq n \), the cluster center of i-th cluster is represented by \( c_i \) (where \( c_i \in \mathbb{R} \)). The probability of any feature point \( x_j \) that belongs to the i-th cluster is measured by its membership value, denoted by \( u_{ij} (0 \leq u_{ij} \leq 1) \), which has the following characteristics:

\[
\sum_{i=1}^{c} u_{ij} = 1, 0 \leq u_{ij} \leq 1, \quad \sum_{j=1}^{n} u_{ij} \geq 0
\]  

The best cluster center in the FCM method can be found by minimizing the following objective function:

\[
J = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2
\]  

where \( d_{ij} = \|c_i - x_j\|_2 \) is the Euclidean distance between the cluster center \( c_i \) and any feature point \( x_j \), and \( m(\geq 1) \) is the fuzziness index that represents the level of cluster fuzziness.

In the process of minimizing the objective function, the cluster center \( c_i \) and the membership value \( u_{ij} \) of all feature points (pixels) are updated iteratively:

\[
c_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m}
\]

\[
u_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \frac{d_{ij}}{d_{ik}} \right)^{2/m}}
\]

For a given image, the image pixels are divided into c clusters based on their similarity that is measured by the membership value \( u_{ij} \). The membership values of all pixels to all c clusters form a membership matrix \( U \). The membership values of the c cluster centers in the membership matrix are used as the basis for classification. Pixels near the center are optimized when they obtain a high membership value, while those that are far away obtain low values. Upon completion of the iteration, the initial contour of the c categories of the image are obtained, based on which, as well as the category of interest, the image is finally segmented with the LSM.

3. Quantum Particle Swarm Optimization (QPSO) Algorithm

The particle swarm optimization (PSO) was first proposed by Kennedy and Eberhart (1995) as a population-based optimization technique, where a population is called a swarm and each individual possible solution to the optimization problem is considered a particle in the swarm [17]. In terms of the PSO, a particle that moves along a trajectory is depicted by its position and velocity in the search space. An optimal solution is found with the guidance of the individual best position (pbest) found by a particle and the global best position (gbest) obtained from the population. A limitation of the conventional PSO is that the solution may easily fall into local optima. In 2004, inspired by the analysis of convergence of PSO, J. Sun et al. studied the individual particle moving in a quantum style and proposed the Quantum Particle Swarm Optimization (QPSO) algorithm [18]. In QPSO, each particle flies in the search space at a certain speed, and dynamically adjusts the particle velocity according to the flight experience of individual particles and particle swarms. Particles update their position according to the following formulations:

\[
p = \frac{\alpha_1 p_{best} + \alpha_2 g_{best}}{\alpha_1 + \alpha_2}
\]

\[
m_{best} = \sum_{i=1}^{N} \frac{p_i}{N}
\]

\[
x(t + 1) = p \pm \beta \cdot |m_{best} - x(t)| \cdot ln(\frac{1}{e})
\]

\[
\beta = 0.5 + 0.5 \cdot \frac{|t_{max} - t|}{t_{max}}
\]

where \( p \) is the optimal particle position, \( \alpha_1 \) and \( \alpha_2 \) are random numbers between zero and one; \( p_{best} \) is the current optimal position of an individual particle, \( g_{best} \) is the current global optimal position of the population, \( m_{best} \) is the average optimal position of the particle swarm; \( N \) is the number of particles in the population; \( p_i \) is the optimal position of the i-th particle; \( \beta \) is the contraction-expansion coefficient, which decreases linearly in the QPSO convergence process, and can control the convergence speed; \( t \) is the current evolutionary generation; \( t_{max} \) is the maximum evolutionary generations; \( x(t) \) is the location information of the particles; \( e \) is a random number between zero and one, which determine the sign of the second term on the right-hand side of the Eq. (7) during the iteration process. When \( e \) is greater than 0.5, a negative sign is taken, otherwise a positive sign.

In QPSO, the position of the particle is updated by Eq. (7). Same with PSO, the position of all particles in QPSO is evaluated with a fitness function to determine the fitness value of the particle at the current position to judge whether the current position is good or bad. The individual best position and the global best position are then updated according to the fitness value. Without loss of generality, we
consider the following minimization problem:

$$\text{minimize} f(x), x \in F \in \mathbb{R}^n$$  \hspace{1cm} (9)

where \( f(x) \) is an fitness function of the minimization problem, and \( F \) is the feasible solution space.

In QPSO, the particles can appear anywhere in the search space, and the probability of their appearance is higher if the position is closer to the local attractor. This mechanism can guarantee the convergence of QPSO, and also equips QPSO with a powerful global search capability.

4. QPSO-FLSM Algorithm

4.1 Algorithm Description

FCM algorithm is essentially a local search algorithm. Due to its shortcomings of falling into the local optima and the algorithm randomly selecting the initial cluster centers [19]–[21], different initial cluster centers lead to different clustering results. The QPSO has global search capabilities, which prevents the solution falling into the local optima. Therefore, this paper combines QPSO with FCM, and proposes the QPSO-FLSM algorithm. This new algorithm takes advantage of the QPSO algorithm’s better global convergence performance instead of FCM iterative process to prevent FCM from falling into the local optima, so as to obtain better overall clustering quality. To evaluate the new combined algorithm, the dice similarity coefficient [22], \( \text{Inter} \) distance and the result of image segmentation will be used as the evaluation indices. The larger the dice similarity coefficient, the higher the similarity between two images. Larger \( \text{Inter} \) distance implies that the similarity between different clusters is smaller. A better result of image segmentation would mean that its segmentation result is closer to the region of interest.

4.2 Effectiveness Analysis of Algorithms

The QPSO-FLSM algorithm is implemented through the following steps:

Step 1:
Determine the number of clusters \( c \) and particles \( n \) (each particle represents \( N_c \) cluster center vectors); Then, the central matrix \( U \) of the cluster is randomly initialized and assigned to each particle. Finally, repeat the above process \( n \) times resulting in a total of \( n \) initial particles.

Step 2:
Initialize the individual and global locations of the particle swarm.

Step 3:
For each particle, the Euclidean metric is used to calculate the distance \( d_{ij} \) between the feature vector \( x_i \) and each of the center vectors contained in the particle. The data are clustered according to the principle of minimum distance and the new cluster centers are calculated. Formula (2) is regarded as the fitness function to update the fitness value of the particle (in this case, \( m \) takes 0).

Step 4:
For each particle, the fitness value in its current position is compared with the fitness value in the best position experienced by itself. If the fitness value in its current position is better than the fitness value in its historical best position, then the best position is updated with the current position to get the \( p_{\text{best}} \).

Step 5:
For each particle, the fitness value in its current position is compared with the fitness value in the best position experienced by the population. If the fitness value in its current position is better than the fitness value in the optimal position experienced by the population, then the optimal position is updated with the current position to get the \( g_{\text{best}} \).

Step 6:
Use Eq. (6) to calculate \( m_{\text{best}} \). Calculate random points according to formula (5) and formula (7) and update the center vector of each particle.

Repeat Step 3 - Step 5 until the conditions for the termination of the loop are satisfied (the center vector changes little or exceeds the maximum number of iterations or the data vector in the cluster does not change any more), and the final clustering result is obtained.

Step 7:
Implement the level set segmentation with the initial contour generated by the above clustering results.

To test the effectiveness of the QPSO-FLSM algorithm, the dice similarity coefficient (formula (10)), fitness value (formula (2)), \( \text{Inter} \) distance (formula (11)) and \( \text{Intra} \) distance (formula (12)) are employed:

$$\text{Dice}(A, B) = \frac{2(|A \cap B|)}{|A| + |B|}$$  \hspace{1cm} (10)

$$\text{Inter} \text{distance} = \|c_i - c_j\|_2$$  \hspace{1cm} (11)

$$\text{Intra} \text{distance} = \frac{1}{|e_i|} \sum_{j=1}^{|e_i|} \|x_j - c_i\|_2$$  \hspace{1cm} (12)

By clustering an image data, the region of interest in the image could be obtained. For a clustering algorithm, the dice similarity coefficient is used to calculate the degree of similarity between experimental segmentation result and expert manual segmentation result. Where \( A \) is the result of experimental segmentation, \( B \) is the result of expert manual segmentation, \( n \) is the number of image pixels, and the range of \( \text{Dice} \) is \([0,1]\). The performance is measured by small fitness value, which imply a stable performance and small error [23]–[25]. For the \( \text{Inter} \) distance, larger distance signifies less similarity between two different clusters, thus, the larger, the better. The \( \text{Intra} \) distance of the cluster indicates the deviation of each member from the cluster center. Thus, the smaller \( \text{Intra} \) distance implies the tighter internal space in the cluster and the higher similarity among all of its members.

In the iterative process, QPSO-FLSM algorithm uses QPSO algorithm and FCM algorithm to find the best clustering result, which is then used as pre-segmentation contour.
for the level set method. Then, the pre-segmentation contour is used as the initial contour of the level set method. Finally, the initial contour is segmented to get the final result. The new algorithm makes use of the global search capability of QPSO to eliminate the possibility that the FCM-selected clustering center falls into the local optimal point. The initial contour resulted from the QPSO-FLSM treatment is closer to the ideal initial contour than that obtained from the FLSM, and the final segmentation showed improved result.

5. Experiment and Discussion

In order to verify the effectiveness of the proposed algorithm, three different types of images are used for testing, including a liver tumor CT image, an MRI slice of brain tissue, and a lightning image. All the algorithms run under the MATLAB2015a environment in Windows 7.

5.1 Effectiveness Analysis of Algorithms

The first experiment is to assess the effectiveness of QPSO-FLSM’s outcome for the contour initialization of the level set. In the experiment, four contour initialization methods were used, including manual demarcation, intensity thresholding, FLSM, and QPSO-FLSM, and then the LSM was used to segment the image [26], [27]. Figure 1 shows the performance comparison among different algorithms to segment the brain tissue MRI image, which have weak border, strong background noise, and mixed interference of white matter (WM) and gray matter (GM). In Fig. 1, it is obvious to see that the manual marked initial contour will produce poor effect (as discussed below) in the final level set segmentation (Fig. 1 A and E). On the contrary, the intensity threshold (Fig. 1 B and F), the FLSM (Fig. 1 C and G), and the QPSO-FLSM (Fig. 1 D and H) could evolve the curve to approach the interest boundary quickly. However, in the case of Fig. 1 C and D, the final segmentation results are highly sensitive to the threshold value, which means deciding a proper threshold is very challenging. For the fuzzy clustering (Fig. 1 C and G) and QPSO-FLSM (Fig. 1 D and H) cases, both can achieve the final segmentation without manual marking area and initializing threshold.

5.2 Segmentation Effect Analysis of the Algorithm

There are five indicators to evaluate the segmentation effect of using the FLSM and the QPSO-FLSM algorithm, namely, the dice similarity coefficient, fitness value, Inter_distance, Intra_distance, and image segmentation result.

In the second experiment, three different images are compared:

- DataSet1: Liver tumor CT image (CT), 200 × 250 pixels, clustering category is set to 3.
- DataSet2: MRI slice of brain tissue (MRI), 200 × 250 pixels, clustering category is set to 4.
- DataSet3: Lightning Picture (Light), 705 × 681 pixels, clustering category is set to 3.

In the experiment, the particle number is set to 20, and the result is obtained by averaging the values of 30 times simulations. Table 1 is the comparison of pre-segmentation effect with the QPSO-FLSM algorithm and the FLSM algorithm respectively, Fig. 2 shows the final LSM segmentation result after the QPSO-FLSM and FLSM algorithm are employed.

In Table 1, the dice similarity coefficient (Dice) reflects that the segmentation result of the QPSO-FLSM algorithm is more similar to the result of expert manual segmentation than FLSM. The convergence generations (CG) of the two algorithms, the convergence speed of the FLSM algorithm is relatively faster than that of the QPSO-FLSM algorithm. Furthermore, the final fitness value (Fit) of the QPSO-FLSM algorithm is smaller than that of the FLSM algorithm and the average reduction is about 10%, which indicates that the QPSO-FLSM algorithm did a better and reliable classification than the FLSM algorithm. Furthermore, from the comparison of Intra_distance (Intra) and Inter_distance

Table 1 Calculation results under different initial clustering center.

| Data  | Algorithm | Dice   | Fit  | CG | Intra | Inter |
|-------|-----------|--------|------|----|-------|-------|
| CT    | FLSM      | 0.9479 | 1.99 | 10 | 75.93 | 0.67  |
|       | QPSO-FLSM | 0.9509 | 1.82 | 16 | 75.94 | 0.66  |
| MRI   | FLSM      | 0.8646 | 7.24 | 15 | 114.63| 1.25  |
|       | QPSO-FLSM | 0.8761 | 6.48 | 20 | 114.68| 1.24  |
| Light | FLSM      | 0.9422 | 1.46 | 15 | 86.69 | 26.07 |
|       | QPSO-FLSM | 0.9574 | 1.31 | 20 | 86.72 | 25.95 |

Fig. 1 Segmentation of MRI cerebral tissues (WM and GM): (A) manual initialization (Green outline); (B) initialization by thresholding; (C) initialization by FLSM; (D) initialization by spatial QPSO-FLSM; (E) A’s final segmentation after 1800 iterations (Red outline); (F) B’s final segmentation after 100 iterations (Red outline); (G) C’s final segmentation after 100 iterations (Red outline); (H) D’s final segmentation after 100 iterations (Red outline).
QPSO-FLSM algorithm in this paper obviously improved the segmentation of tumor images.

Figure 2 B, 2 E and 2 H show the results on a brain tissue MRI image. The white matter and gray matter parts of brain tissue disperse over the entire image slice, and are intertwined with each other, so the WM segmentation gets difficult. Compared with the segmentation with the FLSM algorithm, the segmentation with the proposed algorithm gets improvements by improving the contour initialization and overcoming the over-segmentation or lack-segmentation to some extent, due to combing the advantages of the FLSM and of the QPSO algorithm. Figure 2 C, 2 F and 2 I are for a lighting image, where the proposed algorithm also improved the final segmentation.

5.3 Sensitivity Analysis of Algorithm

It can be concluded from the above experiments that the proposed algorithm in this paper obtains better segmentation results, especially in the liver tumor segmentation. In order to verify the sensitivity of the QPSO-FLSM algorithm, three different initial cluster centers were randomly selected for liver tumor images using FLSM algorithm and QPSO-FLSM algorithm to obtain the initial contour region, and calculate the fitness function values of the two algorithms. Then the LSM algorithm is used to segment the contour of its clustering area, and compare the final segmentation result with the result of expert manual segmentation to calculate the dice similarity coefficient. Finally, the dice similarity coefficient and the fitness value (Fit) are obtained and shown in Table 2 and the image segmentation effect in Fig. 3.

In Fig. 3, the A, B, C images were clustering results using FLSM and QPSO-FLSM algorithm to obtain the initial contour region, and compare the final segmentation result with the result of expert manual segmentation to calculate the dice similarity coefficient.
Fig. 3 Comparison of liver tumor image segmentation with different initial cluster centers (purple curve is the initial contour, red and green curve are the final results). (A) The initial cluster center is (114.48, 0.58, 82.32); (B) the initial cluster center is (114.59, 0.22, 83.41); (C) the initial cluster center is (115.23, 0.50, 90.63); (D) FLSM segmentation results of A; (E) FLSM segmentation results of B; (F) FLSM segmentation results of C; (G) QPSO-FLSM segmentation results of A; (H) QPSO-FLSM segmentation results of B; (I) QPSO-FLSM segmentation results of C.

Fig. 4 Comparison of QPSO-FLSM segmentation results with different level set control parameters

need to be modulated well by human.

Figure 4 shows the segmentation of liver tumors and brain tissue with different level set control parameters. Comparing Fig. 4 B, 4 D (\(v = 0.079, s = 2.531\)) with 4 A, 4 C (\(v = 0.348, s = 0.575\)), it is easy to find that the effect of Fig. 4 B, 4 D (\(v = 0.079, s = 2.531\)) are better than that of Fig. 4 A, 4 C (\(v = 0.348, s = 0.575\)). However, the optimization of control parameters of level set is out of the scope of this paper.

5.5 Performance Analysis of Algorithms

In the QPSO-FLSM algorithm, the number of quantum particles is determined by the complexity of the problem, and the position of the particle group is replaced with the position of the current optimal particles by changing the FCM clustering center formula. With the global nature in search space, the QPSO algorithm can make quantum particles be optimized in the entire solution space, which avoids particles being confined to a local optimum position, and make the fitness values achieve the optimal value. Due to introduction of the quantum algorithm, the complexity of the QPSO-FLSM algorithm will be affected by the dimension problem and the number of particles, which leads to the linear increase of complexity and reduction of the convergence rate. However, the QPSO-FLSM algorithm will eventually converge to the global optimum, and form a stable solution space.

6. Conclusion

In this paper, aiming at improving the FLSM and the LSM algorithm, the QPSO-FLSM algorithm is proposed. The QPSO algorithm is a global search algorithm, and characterized by simple parameters, stable convergence, and ease of implementation.

The experimental results showed that optimizing the FLSM clustering by the QPSO algorithm can get more reli-
able initial contour and better image segmentation in a stable way. While, the total automation of the proposed algorithm has not implemented, such as the clustering number and the level set parameters are determined by prior knowledge, which results in different segmentation results with different control parameters. In the future, it is expected that the QPSO-FLSM algorithm can be further optimized with full automation.

References

[1] D.L. Pham, C. Xu, and J.L. Prince, “Current methods in medical image segmentation,” Annual Review of Biomedical Engineering, vol.2, no.2, pp.315–337, Jan. 2000.

[2] B.N. Li, C.K. Chui, S. Chang, and S.H. Ong, “Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation,” Computers in Biology & Medicine, vol.41, no.1, pp.1–10, Jan. 2011.

[3] Y. Zhang, B.J. Matuszewski, L.-K. Shark, and C.J. Moore, “Medical image segmentation using new hybrid level-set method,” Fifth International Conference Biomedical Visualization: Information Visualization in Medical and Biomedical Informatics, pp.71–76, July 2008.

[4] S. Osher and R.P. Fedkiw, Level Set Methods: An Overview and Some Recent Results, Academic Press Professional, Inc., May 2001.

[5] A. Jinda-Apiraksa, S.H. Ongt, L.T. Hiew, K.W.C. Foong, and T. Kondo, “A segmentation technique for maxillary sinus using the 3-d level set method,” TENCON 2009 - 2009 IEEE Region 10 Conference, pp.1–6, Nov. 2009.

[6] X. Yang, X. Gao, D. Tao, X. Li, and J. Li, “An efficient mrf embedded level set method for image segmentation,” IEEE Trans. Image Process., vol.24, no.1, pp.9–21, Nov. 2014.

[7] N. Paragios, “A level set approach for shape-driven segmentation and tracking of the left ventricle,” IEEE Trans. Med. Imag., vol.22, no.6, pp.773–776, June 2003.

[8] K.-L. Wu and M.-S. Yang, “Alternative c-means clustering algorithms,” Pattern Recognition, vol.35, no.10, pp.2267–2278, Oct. 2002.

[9] K.-S. Chuang, H.-L. Tzeng, S. Chen, J. Wu, and T.-J. Chen, “Fuzzy c-means clustering with spatial information for image segmentation,” Computerized Medical Imaging and Graphics, vol.30, no.1, pp.9–15, Jan. 2006.

[10] W. Cai, S. Chen, and D. Zhang, “Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation,” Pattern Recognition, vol.40, no.3, pp.825–838, March 2007.

[11] M. Rastgarpour, J. Shanbehzadeh, and H. Soltanian-Zadeh, “A hybrid method based on fuzzy clustering and local region-based level set for segmentation of inhomogeneous medical images,” Journal of Medical Systems, vol.38, no.8, pp.1–15, Aug. 2014.

[12] Y. Cai, J. Sun, J. Wang, Y. Ding, N. Tian, X. Liao, and W. Xu, “Optimizing the codon usage of synthetic gene with qpso algorithm,” Journal of Theoretical Biology, vol.254, no.1, pp.123–127, Sept. 2008.

[13] J. Sun, W. Xu, and B. Feng, “A global search strategy of quantum-behaved particle swarm optimization,” Cybernetics and Intelligent Systems, 2004 IEEE Conference on IEEE Xplore, pp.111–116, Dec. 2004.

[14] C. Huang, D. Zhang, and G. Song, “Low-power mapping algorithm for three-dimensional network-on-chip based on diversity-controlled quantum-behaved particle swarm optimization,” Journal of Algorithms & Computational Technology, vol.10, no.3, pp.176–186, June 2016.

[15] G.R. Reddy, K. Ramudu, S. Zaheeruddin, and R.R. Rao, “Image segmentation using kernel fuzzy c-means clustering on level set method on noisy images,” International Conference on Graphic and Image Processing, pp.522–526, Feb. 2011.

[16] C. Huang, B. Yan, H. Jiang, and D. Wang, “Mr image segmentation based on fuzzy c-means clustering and the level set method,” International Conference on Fuzzy Systems and Knowledge Discovery, pp.67–71, Oct. 2008.

[17] H. Gao, W. Xu, J. Sun, and Y. Tang, “Multilevel thresholding for image segmentation through an improved quantum-behaved particle swarm algorithm,” IEEE Trans. Instrum. & Measurement, vol.59, no.4, pp.934–946, May 2010.

[18] J. Sun, B. Feng, and W. Xu, “Particle swarm optimization with particles having quantum behavior,” Proceedings of 2004 Congress on Evolutionary Computation, pp.325–331, June 2004.

[19] J. Yu, P. Guo, P. Chen, Z. Zhang, and W. Ruan, “Remote sensing image classification based on improved fuzzy c-means,” Geo-spatial Information Science, vol.11, no.2, pp.90–94, June 2008.

[20] X. Tong, S. Zeng, J. Ou, and B. Wan, “Two-stage fuzzy c-mean cluster and its applications,” Journal of Huazhong University of Science & Technology, vol.36, pp.71–75, Nov. 2008.

[21] Q.M. Xie and Y.Y. Xia, “Dynamic clustering method for evaluation of slope stability based on genetic algorithms,” Rock & Soil Mechanics, vol.23, no.2, pp.170–172+178, April 2002.

[22] S.K. Warfield, K.H. Zou, and W.M. Wells, “Validation of image segmentation by estimating rater bias and variance,” Medical Image Computing and Computer-Assisted Intervention, vol.4191, pp.839–847, Sept. 2008.

[23] G. Hamerly and C. Elkan, “Alternatives to the k-means algorithm that find better clusterings,” Proceedings of the eleventh international conference on Information and knowledge management, pp.600–607, Jan. 2002.

[24] M. Omran, A.P. Engelbrecht, and A. Salman, “Particle swarm optimization method for image clustering,” International Journal of Pattern Recognition & Artificial Intelligence, vol.19, no.3, pp.297–321, May 2005.

[25] M.J. Li, M.K. Ng, Y. Cheung, and J.Z. Huang, “Agglomerative fuzzy k-means clustering algorithm with selection of number of clusters,” IEEE Transactions on Knowledge & Data Engineering, vol.20, no.11, pp.1519–1534, Nov. 2008.

[26] C. Li, C. Xu, C. Gui, and M.D. Fox, “Level set evolution without re-initialization: A new variational formulation,” International Conference on Fuzzy Systems and Knowledge Discovery, pp.430–436, June 2005.

[27] C. Li, C. Xu, K.M. Konwar, and M.D. Fox, “Fast distance preserving level set evolution for medical image segmentation,” International Conference on Control, Automation, Robotics and Vision, pp.1–7, Jan. 2006.
**Yuanqi Fu** received B.S. degree in Chengdu University of Information Technology in 2016. She is presently a M.S. candidate in Electronic and Communication Engineering at the Electronic Engineering College of Chengdu University of Information and Technology. Her research interest is in image processing.

**Zhongke Wang** received B.S. degree in Chengdu University of Meteorology in 1994. He is presently at Chengdu University of Information and Technology. His research interests are in image processing and new weather radar algorithms.

**Xiaoqiong Zhen** received B.S. degree in Electronic Engineering from Nanjing Forestry University in 2006 and M.S. degree in Signal and Information Processing from Chengdu University of Information and Technology (CUIT) in 2010. She is presently a Ph.D. candidate in Atmospheric Physics and Atmospheric Environment at the Institute of Atmospheric Physics, Chinese Academy of Sciences. She is also a lecturer at CUIT. Her research interests include atmospheric sounding and high temporal- and spatial-resolution detection of small mesoscale precipitation observation and analysis.

**Zhipeng Yang** received M.S. degree in Signal and Signal Processing from Chengdu University of Information and Technology (CUIT) in 2010. Currently, he is a Ph.D. candidate at Sichuan University and also a lecturer at CUIT. His research focuses on processing and analysis of magnetic resonance images and clinical applications.

**Xingang Fan** received Ph.D. degree in Atmospheric Sciences from Lanzhou University in 1996. He is an Associate Professor of Meteorology in the Department of Geography and Geology at the Western Kentucky University. He is also a visiting professor at the Institute of Atmospheric Physics, Chinese Academy of Sciences and the Chengdu University of Information Technology.