ISSN : 0974 - 7435 Volume 10 Issue 23

2014

BioTechnology
An Indian Journal

FULL PAPER

BTAIJ, 10(23), 2014 [14483-14491]

Self-adapted fuzzy C-means segmentation algorithm based on bacterial chemotaxis

Li Yanling*, Li Gang
College of Computer and Information Technology, Xinyang Normal University, Xinyang 464000, (CHINA)
E-mail:lyl75@163.com

ABSTRACT

Although fuzzy c-means algorithm is one of the most popular methods for image segmentation, it is in essence a technology of searching local optimal solution and sensitive to initial data. For this, self-adapted fuzzy c-means segmentation algorithm based on bacterial chemotaxis is proposed in this paper. In the new algorithm, self-adapted fuzzy c-means algorithm is used to get the initial number of clusters and bacterial chemotaxis algorithm is used for avoiding falling into local optimization. Experimental results show that the proposed algorithm used for image segmentation can segment images more effectively and can provide more robust segmentation results.

KEYWORDS

Fuzzy C-means algorithm; Bacterial chemotaxis; Bacterial colony chemotaxis, Hybridized bacterial chemotaxis; Self-adapted.

INTRODUCTION

Image segmentation is one of the most difficult and challenging problems in the image processing. It denotes a process by which an image is partitioned into non-overlapping regions such that each region is homogeneous and the union of two adjacent is heterogeneous. The extent of homogeneity of the segmented region can be measured using some image property (eg. Pixel intensity[1]). Most of segmentation algorithms aim at the concrete problem; there is not a universal segmentation method for all images.

Clustering can be defined as the optimal partitioning of a given set of n data points into c subgroups, such that data points belonging to the same group are as similar to each other as possible whereas data points from two different groups have the maximum difference. Image segmentation can be treated as a clustering problem where the features describing a pixel correspond to a pattern, and each image region corresponds to a cluster. Therefore many clustering algorithms have widely been used to solve the segmentation problem (eg., K-means[2], FCM, ISODATA [3] and Snob [4]). In the last decades, fuzzy segmentation methods, especially the fuzzy c-means algorithm (FCM) [5], have been widely used in the image segmentation [6,7] and such a success chiefly attributes to introduction of fuzziness for the belongingness of each image pixel, which makes the clustering methods able to retain more information from the original image than the crisp or hard segmentation methods [8].However, most of the unsupervised fuzzy clustering algorithms assume a prior knowledge of the number of classes, c, while in many practical situations, the appropriate number of classes is unknown or impossible to determine even approximately. Find an optimal number of clusters in a large dataset is usually a challenging task.

Because the fuzzy partitions obtained using the FCM algorithm depend on the choice of c. It is necessary to validate each of the fuzzy c-partitions once they are found [9]. This validation is carried out by a cluster validity index, which evaluates each of the fuzzy c-partitions and determines the optimal partition or the optimal number clusters (c) from them. Many validation criteria have been proposed for evaluating fuzzy partitions [10], such as Bezdek's partition coefficient (Vpc) and partition entropy (Vpe), Xie-Beni's Vxb, Fukuyama-Sugeno's VFS , Kwoņ's VK , Boudraa's VCWB and Dae-WonKim's VOS . Researchers use nests ISODATA and GA to get the optimal partition according to various validation criteria. However, it is necessary to pre-define the maximum number of clusters (c) when we use the exhaustive attack method to get the optimal partition number. Obviously, the exhaustive attack method is feasible when the data point is less. But the exhaustive attack method is impossible when the data point is big. Moreover, we have not a generic theory and implement method to determine the maximum number of clusters (c) at present. In [10], a new cluster validity index is proposed that determines the optimal partition and optimal number of clusters for fuzzy partitions obtained from the fuzzy c-means algorithm. The proposed validity index exploits an overlap measure and a separation measure between clusters. In[11], the authors use a fuzzy cluster validity metric proposed by Xie and Beni as the criterion for evaluating a partition produced by swarm based clustering. In[12,13], colony algorithm is used to get the initial cluster centers.

In this article, self-adapted fuzzy c-means segmentation algorithm based on bacterial chemotaxis is proposed, which can determine the number of clusters automatically by means of a new validity function. In addition, bacterial chemotaxis algorithm is used for avoiding falling into local optimization in this paper. Experimental results show that the proposed algorithm used for image segmentation can segment images more effectively and can provide more robust segmentation results.

The rest of the paper is organized as follow. In section 2, we briefly outline the self-adapted fuzzy c-means segmentation algorithm. Bacterial chemotaxis algorithm is proposed in section 3. In section 4, we proposed the self-adapted fuzzy c-means segmentation algorithm based on bacterial chemotaxis. The experimental results and evaluations are presented in section 5. In section 6, we conclude this paper.

SELF-ADAPTED FUZZY C-MEANS ALGORITHM

In the present study, we define the dataset

$$X = \{x_1, x_2, \cdots, x_n\} \in R^d \quad (1)$$

Where $x_k = [x_{1k}, x_{2k}, \cdots, x_{dk}]^T \in R^d$, n is the card of dataset X , c is the number of clusters to be explored, and $1 < c < n$, v is the dataset of the clustering centre, and $v_j \in R^d (1 \le j \le c)$, $d_{ij} = \|x_j - v_i\|$ is the Euclidean distance between x_j and v_i, u_{ij} is the membership value from x_j to v_i. $U = [u_{ij}]_{c \times n}$, $V = [v_{ij}]_{d \times c}$.

The fuzzy clustering problem can be formulated as the following mathematical programming problem. The objective function is as $J_m(U,V) = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^m d_{ij}^2$, which is subject to $\sum_{i=1}^{c} u_{ij} = 1, \quad 1 \le j \le n \quad 0 < \sum_{j=1}^{n} u_{ij} < n \quad 1 \le i \le c \quad \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij} = n$. Where m is the fuzzy weighting exponent, which is any real number greater than 1.

A good partition should satisfy two requirements: (1) The inter-cluster distances should be as bigger as possible; (2) The intra-cluster distances should be as smaller as possible. The above two requirements are the criterion of the clustering validity. According to this guideline, we constructed the following new validity function:

$$L(c)=\frac{\sum_{i=1}^{c}\left(\sum_{j=1}^{n}u_{ij}^{m}\right)\left\|v_i-\bar{v}\right\|^2(n-c)}{\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}\left\|x_j-v_i\right\|^2(c-1)} \qquad (2)$$

Where $\bar{v}$ is the mean value of the Clustering centre v_i, that is:

$$\bar{v}=\frac{1}{c}\sum_{i=1}^{c}v_i \qquad (3)$$

The numerator of $L(c)$ denotes the sum of the distances between classes and the denominator of $L(c)$ denotes the sum of the intra-distances of all the clusters. So the bigger $L(c)$ is, the more reliable the result of clustering is.

The step of self-adapted fuzzy c-means algorithm is presented below:

1) Initialization

2) The partition matrix $U_{ij}^{(k)}=1/\sum_{r=1}^{c}(\frac{d_{ij}^{(k)}}{d_{rj}^{(k)}})^{\frac{2}{m-1}}$ was constructed.

3) The prototypes $v_i^{(k+1)}=(\sum_{j=1}^{n}(u_{ij}^{(k)})^m x_j)/(\sum_{j=1}^{n}(u_{ij}^{(k)})^m)$ was calculated.

4) If $\left\|V^{(k+1)}-V^{(k)}\right\|\le\varepsilon$, then stop the iteration, else let $k=k+1$,and go to Step 2. $\|\bullet\|$ is some kind of matrix norm.

5) $L(c)$was calculated under $2<c<n$. If $L(c)$ is the highest values, then stop the algorithm, else go to Step 2 with $c=c+1$.

With self-adapted fuzzy c-means algorithm, the number of clusters is determined automatically. But fuzzy c-means algorithm is easy in local optimum when it is used for image segmentation. For this, self-adapted fuzzy c-means segmentation algorithm based on swarm intelligence is proposed. In the new algorithm, swarm intelligence algorithm is used to avoid falling into local optimization.

BACTERIAL CHEMOTAXIS ALGORITHM

Bacterial chemotaxis (BC) algorithm is a newly developed stochastic gradient evolutionary algorithm. Differed from the interaction models for behavior of social insects, bacteria is considered individual and social interaction is not used in the model. The movement of bacteria depends on its direction and the duration of the next movement step while this information is obtain by comparing an environmental property at two different time steps. On account of its simplicity and robustness, this evolution strategy is worthy of further research.

In order to describe the optimization algorithm of bacterial chemotaxis clearly, the motion of a single bacterium in two dimensions is as follows. The strategy in n-dimension can be found in [14]. BC is presented below:

1) Compute the velocity v which is assumed to be a constant value

$$v=const \qquad (4)$$

2) Compute the duration of the trajectory τ from the distribution of a random variable with an exponential probability density function

$$P(X=\tau)=\frac{1}{T}e^{-\tau/T} \qquad (5)$$

The time T is given by

$$T=\begin{cases}T_0, & for\ \frac{f_{pr}}{l_{pr}}>=0\\ T_0\left(1+b\left|\frac{f_{pr}}{l_{pr}}\right|\right), & for\ \frac{f_{pr}}{l_{pr}}<0\end{cases} \qquad (6)$$

Where T_0 is the initial mean time; f_{pr} is the difference between the actual and the previous function value; l_{pr} is the length of the previous step; b is the dimensionless parameter.

3) Compute the new direction. The probability density distribution of the angle α between the previous and the new direction is Gaussian and reads, for turning right or left, respectively

$$P(X=\alpha,v=\mu)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left[-\frac{(\alpha-v)^2}{2\sigma^2}\right] \qquad (7a)$$

$$P(X=\alpha, v=-\mu)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left[-\frac{(\alpha-v)^2}{2\sigma^2}\right] \quad (7b)$$

Where the expectation value is $\mu = E(X) = 62^0$ and the standard deviation is $\sigma = \sqrt{Var(X)} = 26^0$. When $f_{pr}/l_{pr} < 0$, the variation of the expectation value and the variance are indicated as follows:

$$\mu = 62^0(1-\cos(\theta)) \quad (8)$$

$$\sigma = 26^0(1-\cos(\theta)) \quad (9)$$

$$\cos(\theta) = e^{-\tau_c \tau_{pr}} \quad (10)$$

Where τ_c is the correlation time, and τ_{pr} is the duration of the previous step.

4) Compute the new position.

$$\overrightarrow{x_{new}} = \overrightarrow{x_{old}} + \overrightarrow{n_u} l \quad (11)$$

Where the length of the path l is given by $l = vt$ and the normalized new direction vector is $\overrightarrow{n_u}$. In summary, there are four parameters to be determined: T_0, b, τ_c, v. In order to improve the algorithm, the automatic change of all strategy parameters is adapted during the optimization.

SELF-ADAPTED FUZZY C-MEANS SEGMENTATION ALGORITHM BASED ON BACTERIAL CHEMOTAXIS

Self-adapted fuzzy C-means segmentation algorithm based on bacterial colony chemotaxis

Generally speaking, BC algorithm is a stochastic gradient search strategy because the trajectory only depends on the information of previous step or several steps before. For its randomness, this optimization algorithm can prevent the search process form falling into the local optimal solution and becoming premature convergence. Whereas, some shortcomings still exist as a stochastic optimization strategy based on individual search. Firstly, single individual gathers limited gradient information during the search and it will waste too much time at the beginning of optimization. Meanwhile, when the difference of gradient between the previous and current step is below a certain constant, individuals will move stochastic [15]. With the precision become higher, the searching space cannot be ensured in the neighbourhood of global optimal solution.

For this reason, bacterial colony chemotaxis (BCC) algorithm is proposed in this paper. BCC algorithm much improves the performance of BC algorithm while possessing the searching ability of a single bacterium, making it comparable to many other well-used intelligent optimization methods.In the BCC algorithm, the update method of target precision is improved. The original equidifferent update method is replaced by update method of series. The step of BCC algorithm is presented below:

1) Repeat

2) Initialization

3) If bacterial *i* is in *k* moves, it need perceive other bacteria which are in better position, ascertain their center $center\left(\overrightarrow{x_{i,k}}\right)$, confirm the length $rand(\ )\cdot dis\left(\overrightarrow{x_{i,k}}, center\left(\overrightarrow{x_{i,k}}\right)\right)$ to center $center\left(\overrightarrow{x_{i,k}}\right)$, and ascertain position $\vec{x}\,'_{i,k+1}$

4) If bacterial *i* is in *k* moves, it need ascertain the position $\vec{x}\,''_{i,k+1}$ in k+1 moves by use of BC algorithm

5) Calculate the function value of $\vec{x}\,'_{i,k+1}$ and $\vec{x}\,''_{i,k+1}$. If $f(\vec{x}\,'_{i,k+1}) < f(\vec{x}\,''_{i,k+1})$, bacterial move to $\vec{x}\,'_{i,k+1}$, otherwise it move to $\vec{x}\,''_{i,k+1}$

6) Until a better solution is found or the maximum iteration number reached

Because BCC algorithm is a stochastic gradient search strategy, elite reserved strategy is introduced in it, which can improve the performance of BC and avoid discarding the point with better position. After flora move every step, bacterial with worst position move to bacterial with best position before the whole flora move in the new algorithm. Formula is presented below:

$$\overrightarrow{x_{worst}} = \overrightarrow{x_{worst}} + rand()\cdot(\overrightarrow{x_{best}} - \overrightarrow{x_{worst}}) \quad (12)$$

$rand()$ is normal distribution in (0,2).

In the last decades, fuzzy segmentation methods, especially the fuzzy c-means algorithm (FCM), have been widely used in the image segmentation. However, it is sensitive to initial data, and gets in the local optimization easily. Therefore, choosing a good set of initial cluster centers is very important for FCM algorithm. It can reduce the number of iterations and improve the system performance when selecting a set of initial cluster centers that approximate the actual cluster centers. For this, self-adapted fuzzy c-means algorithm is used to get the initial cluster centers of FCM algorithm firstly, then the output of the AFCM algorithm is used to perform the self-adapted fuzzy c-means cluster segmentation algorithm based on bacterial colony chemotaxis algorithm(AFCM-BCC). The step of AFCM-BCC algorithm is presented below:

1) Given a fixed number , acceleration constants and , inertia weight and , biggest iterative time .

2) perform self-adapted fuzzy c-means algorithm (AFCM).

3) The results of AFCM algorithm is used as the initial cluster centers of self-adapted fuzzy c-means cluster segmentation algorithm based on bacterial colony chemotaxis algorithm (AFCM-BCC). Segment image by using the self-adapted fuzzy c-means cluster segmentation algorithm based on bacterial colony chemotaxis algorithm(AFCM-BCC).

Self-adapted fuzzy C-means segmentation algorithm based on hybridized bacterial chemotaxis

Generally speaking, bacterial chemotaxis algorithm is a stochastic gradient search strategy because the trajectory only depends on the information of previous step or several steps before. Because the new movement direction and sustained time are all decided by probability in BC algorithm, this optimization algorithm can prevent becoming premature convergence. However, BC algorithm is not the optimization algorithm based on swarm intelligence which just depends on the movement behaviour of single bacterial by feeling the change of its surrounding environment constantly. Moreover, BC algorithm just use the past experience to find the optimal value. So BC algorithm has the following defects. Firstly, a single bacteria must amend and simulate the formative gradient information by searching different points in solution space. So the optimization speed of BC algorithm is slow on many issues. Meanwhile, when the difference of gradient between the previous and current step is below a certain constant, bacterial individuals will move stochastic. With the precision become higher, the searching space cannot be ensured in the neighborhood of global optimal solution. PSO algorithm is a efficient population-based optimization technique with high searching speed whose particles adapts their positions by using their own experience as well as the whole swarm's. However, PSO algorithm is easy to premature convergence.

In view of the respective advantages and disadvantages of the above two optimization algorithm, hybridized bacterial chemotaxis(HBC) is proposed in this paper which combines BC algorithm with PSO algorithm. In the proposed self-adapted fuzzy c-means cluster segmentation algorithm based on hybridized bacterial chemotaxis(AFCM-HBC), initial cluster centers of FCM algorithm is get by AFCM algorithm. Then, HBC algorithm is used to image segmentation, in which PSO is introduced to execute the global search first and then stochastic local search works by BC. Meanwhile, elitism preservation is used in the paper. The step of AFCM-HBC algorithm is presented below:

1) Given a fixed number, acceleration constants and, inertia weight and, biggest iterative time.

2) perform self-adapted fuzzy c-means algorithm (AFCM).

3) The results of AFCM algorithm is used as the initial cluster centers of self-adapted fuzzy c-means cluster segmentation algorithm based on hybridized bacterial chemotaxis (AFCM-HBC). Segment image by using the self-adapted fuzzy c-means cluster segmentation algorithm based on hybridized bacterial chemotaxis (AFCM-HBC).

EXPERIMENT RESULTS

In this section, we describe the experimental results on standard test image. There are a total of three algorithms used in this section, i.e., self-adapted fuzzy c-means cluster segmentation algorithm(AFCM), self-adapted fuzzy c-means cluster segmentation algorithm based on bacterial colony chemotaxis algorithm(AFCM-BCC) and self-adapted fuzzy c-means cluster segmentation algorithm based on hybridized bacterial chemotaxis(AFCM-HBC). For all cases, unless otherwise stated, parameters $m = 2$ $\rho = 0.8$.

In order to obtain a quantitative comparison, two types of cluster validity functions, fuzzy partition and feature structure, are used to evaluate the performance of clustering in different clustering methods.

Our first experiment applies the three algorithms to images which are degraded by 2% Gaussian noise. The three imags are cameraman image, rice image and mri brain image. Fig.1 (a), Fig.2 (a) and Fig.3 (a) are original images with 2% Gaussian noise. Fig.1 (b), Fig.2 (b) and Fig.3 (b) show the segmentation results using AFCM algorithm. The segmentation results using AFCM-BCC algorithm are showed in Fig.1 (c), Fig.2 (c) and Fig.3 (c). Fig.1 (d), Fig.2 (d) and Fig.3 (d) show the segmentation results using AFCM-HBC algorithm. Table 1 tabulates the quantitative result of the three algorithms on images with 2% Gaussian noise.

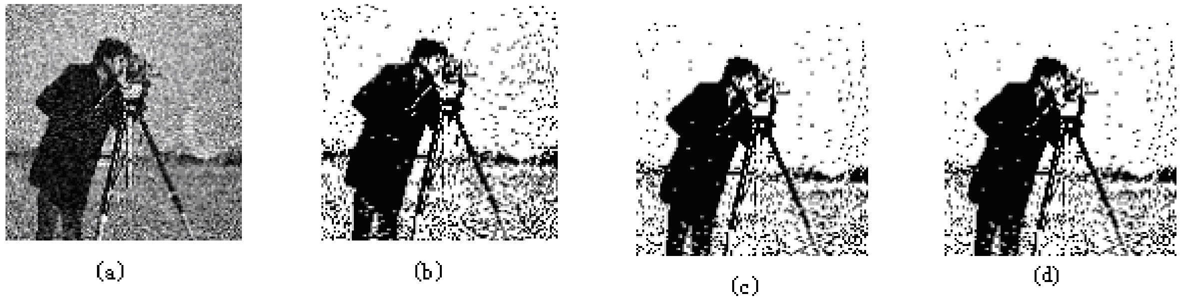

Figure 1 : Comparison of segmentation results on cameraman image with 2% Gaussian noise. (a) image with 2% Gaussian noise (b) AFCM result (c) AFCM-BCC result (d) AFCM-HBC result

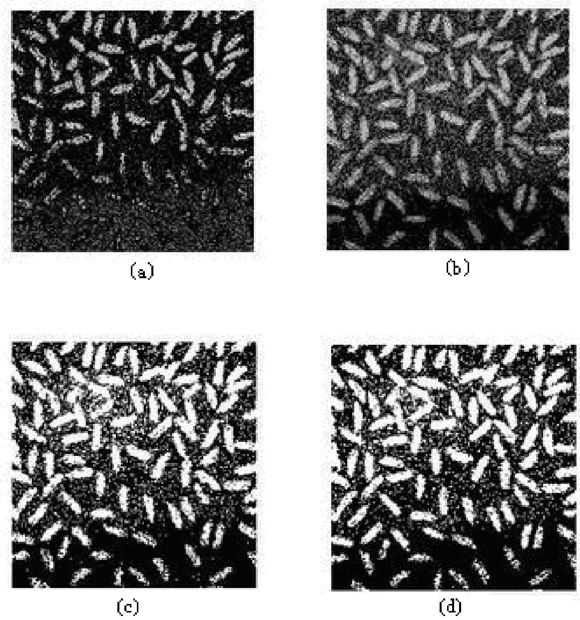

Figure 2 : Comparison of segmentation results on rice image with 2% Gaussian noise. (a) image with 2% Gaussian noise (b) AFCM result (c) AFCM-BCC result (d) AFCM-HBC result

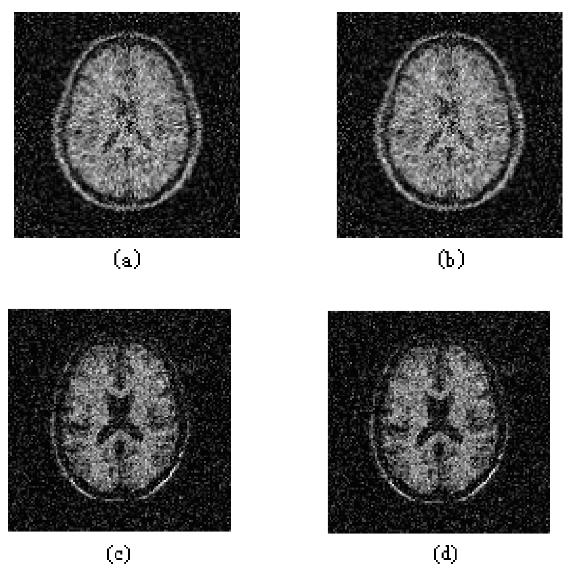

Figure 3 : Comparison of segmentation results on mri brain image with 2% Gaussian noise. (a) image with 2% Gaussian noise (b) AFCM result (c) AFCM-BCC result (d) AFCM-HBC result

TABLE 1: The experimental results of the three algorithms for images with Gaussian noise

image	algorithm	*Vpc*	*Vpe*	*Vxb*
cameraman image	AFCM	0.8599	0.2374	0.0625
	AFCM-BCC	0.8603	0.2371	0.0624
	AFCM-HBC	0.8604	0.2367	0.0622
rice image	AFCM	0.8287	0.2817	0.0891
	AFCM-BCC	0.8297	0.2813	0.0889
	AFCM-HBC	0.8301	0.2808	0.0887
mri brain image	AFCM	0.8795	0.2037	0.0541
	AFCM-BCC	0.8800	0.2032	0.0538
	AFCM-HBC	0.8802	0.2031	0.0536

Second experiment applies the three algorithms to images which are degraded by 2% salt & pepper noise. The three imags are cameraman image, rice image and mri brain image. Fig.4 (a), Fig.5 (a) and Fig.6 (a) are original images with 2% Gaussian noise. Fig.4 (b), Fig.5 (b) and Fig.6 (b) show the segmentation results using AFCM algorithm. The segmentation results using AFCM-BCC algorithm are showed in Fig.4 (c), Fig.5 (c) and Fig.6 (c). Fig.4 (d), Fig.5 (d) and Fig.6 (d) show the segmentation results using AFCM-HBC algorithm. Table 2 tabulates the quantitative result of the five algorithm on images with 2% salt & pepper noise.

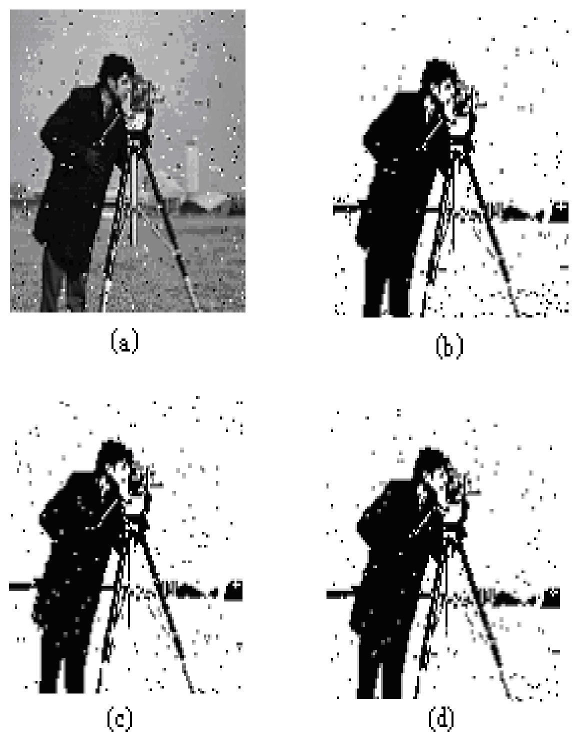

Figure 4 : Comparison of segmentation results on cameraman image with 2% salt & pepper noise. (a) image with 2% salt & pepper noise (b) AFCM result (c) AFCM-BCC result (d) AFCM-HBC result

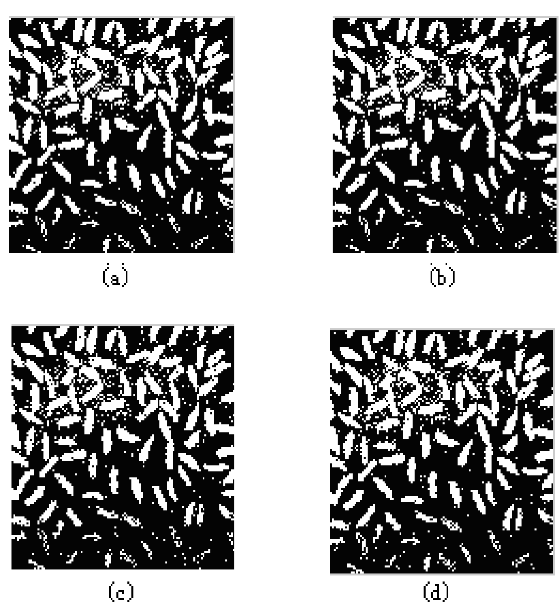

Figure 5 : Comparison of segmentation results on rice image with 2% salt & pepper noise. (a) image with 2% salt & pepper noise (b) AFCM result (c) AFCM-BCC result (d) AFCM-HBC result

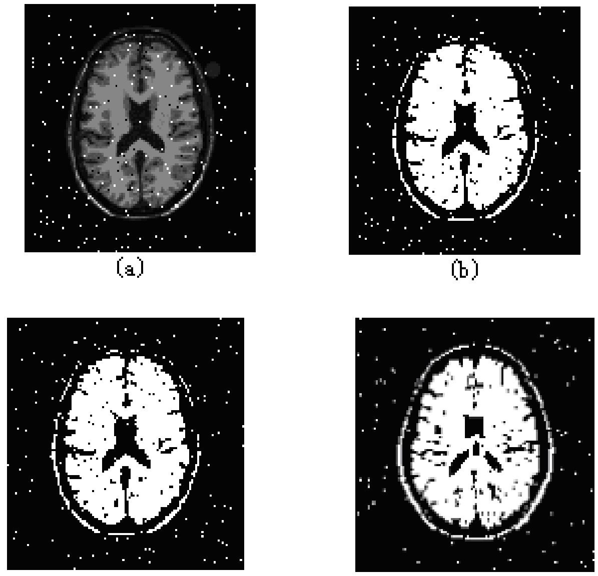

Figure 6 : Comparison of segmentation results on mri brain image with 2% salt & pepper noise. (a) image with 2% salt & pepper noise (b) AFCM result (c) AFCM-BCC result (d) AFCM-HBC result

TABLE 2: The experimental results of the three algorithms for images with salt & pepper noise

image	algorithm	*Vpc*	*Vpe*	*Vxb*
cameraman image	AFCM	0.9232	0.1376	0.0320
	AFCM-BCC	0.9235	0.1373	0.0317
	AFCM-HBC	0.9237	0.1371	0.0315
rice image	AFCM	0.8784	0.2069	0.0636
	AFCM-BCC	0.8788	0.2067	0.0633
	AFCM-HBC	0.8790	0.2065	0.0631
mri brain image	AFCM	0.9380	0.1019	0.0560
	AFCM-BCC	0.9385	0.1008	0.0543
	AFCM-HBC	0.9391	0.1003	0.0536

From the experiment results described above, we can see that AFCM-HBC algorithm is better. For V_{pc} , the AFCM-HBC algorithm is greater. For V_{pe} and V_{xb} , the AFCM-HBC algorithm is smaller. These show that AFCM-HBC algorithm outperform AFCM algorithm and AFCM-BCC algorithm from quantitative results. Additionally, the quality of Fig.1(d)- Fig.6(d) are all superior to other segmentation results visually. All these results indicate that AFCM-HBC algorithm is effective method and outperform AFCM algorithm and AFCM-BCC algorithm.

CONCLUSIONS

FCM algorithm is one of the most popular methods for image segmentation. However, it is in essence a technology of searching local optimal solution and sensitive to initial data. For solving the above problems, self-adapted fuzzy c-means segmentation algorithm based on bacterial chemotaxis is proposed. In the new algorithm, AFCM algorithm is used for getting the initial number of clusters. In addition, bacterial chemotaxis algorithm is used for avoiding falling into local optimization in this paper. Experimental results show that the proposed algorithm used for image segmentation can segment images more effectively and can provide more robust segmentation results.

ACKNOWLEDGEMENT

The authors would like to thank the anonymous reviewers for their helpful comments and suggestions to improve the presentation of the paper. This research is supported by the National Natural Science Foundation of China (61202194), Project of Science and Technology of Henan Province (102300410142) and the Science and Technology Innovation Talent Support Plan of colleges and universities in Henan Province (2011HASTIT026).

REFERENCES

[1] J.C.Dunn; A fuzzy relative of the ISODATA process and its use in detecting compact, well-separated clusters, J.Cybern, 3, 32-57(1974).
[2] Tou J.T., Gonzalez R.C.; Pattern Recognition Principles, Addison-Wesley: London,(1974).
[3] G.. Ball, D. Hall; A clustering technique for summarizing multivariate data, Behavioral Science, 12, 153-155,(1967).
[4] Wallace, C.S., Boulton, D.M.; An information measure for classification, Computer Journal, 11, 185-194(1968).
[5] J.C. Bezdek; Pattern Recognition with Fuzzy Objective Function Algorithms, Plenum Press: New York,(1981).
[6] E.A. Zanaty; Determining the number of clusters for kernelized fuzzy c-means algorithms for automatic medical image segmentation, Egyptian Informatics Journal, 13, 39-58(2012).
[7] Yanling Li, Yi Shen; An automatic fuzzy c-means algorithm for image segmentation, Soft Computing, 14, 123-128(2010).
[8] D.L. Pham, J.L. Prince; An adaptive fuzzy c-means algorithm for image segmentation in the presence of intensity inhomogeneities, Pattern Recognition Letters, 20, 57-68(1999).
[9] Pal, NR, Bezdek, JC; On cluster validity for the fuzzy c-means model, IEEE Trans. Fuzzy Syst, 3, 370-379(1995).
[10] Kim, DW, Lee, KH , Lee, D; On cluster validity index for estimation of optimal number of fuzzy clusters, Pattern Recognition, 37, 2009-2024(2004).
[11] Xulei Yang, Aize Cao , Qing Song; A new cluster validity for data clustering, Neural Processing Letters, 23, 325-344(2006).
[12] Hall, LO, Kanade, PM; Fuzzy ants and clustering, IEEE Trans on Systems, Man and Cybernetics_PART A: Systems and humans, 37, 758-769(2007).
[13] Huang Guo-rui , Wang Xu-fa , Cao Xian-bin; Ant colony optimization algorithm based on directional pheromone diffusion, Chinese Journal of Electronics, 15, 447-450(2006).
[14] S.D. Muller, J. Marchetto, S. Airaghi; Optimization based on bacterial chemotaxis, IEEE Transaction of Evolutionary Computation, 6, 16-29(2002).
[15] W.W.,Li, H.Wang., Z.J.Zhang; Function optimization method based on bacterial colony chemotaxis, Journal of Circuits and Systems, 10, 58-63(2005).