Spatial Information based Image Clustering with A Swarm Approach

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ABSTRACT

Fuzzy c-means algorithm (FCM) is one of the most used clustering methods for image segmentation. However, the conventional FCM algorithm presents some limits like its sensitivity to the noise because it does not take into consideration contextual information and its convergence to local minimum since it is based on a gradient descent method. In this paper, we present a new spatial fuzzy clustering algorithm optimized by the Artificial Bee Colony (ABC) algorithm. ABC-SFCM has two major characteristics. First it tackles better noisy image segmentation by making use of the spatial local information into the membership function. Secondly, it improves the global performance by taking advantages of the global search capability of ABC. Experiments with synthetic and real images show that ABC-SFCM is robust to noise compared to other methods.

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1. INTRODUCTION

Image segmentation is an important step of image analysis. The task of image segmentation can be formulated as a clustering process by which a digital image is divided into multiple meaningful non-overlapping regions [1-2]. The hard clustering partitions the dataset into clusters such that one object exactly belongs to only one cluster. The fuzzy clustering assigns each data point to all different clusters with some degrees of membership. The iterative unsupervised Fuzzy C-Means (FCM) algorithm is the most widely used clustering algorithm for image segmentation [3, 4, 5, 6, 7]. However, since the FCM algorithm does not take into account the contextual information, it is too sensitive to the noise and other imaging artefacts [8,9,10]. To deal with this problem, lots of researchers have introduced some modifications to the conventional FCM algorithm to incorporate spatial information. Urso *et al.* [11] have introduced the weighted fuzzy c-means to find homogeneous groups for fuzzy data. Yang *et al*. [12] proposed the robust deterministic annealing based FCM algorithm to improve the robustness against noisy. Siyal *et al.* [13] introduced modified FCM for automated segmentation of medical images to deal the intensity in-homogeneities and Gaussian noise effectively. A modified FCM which incorporates the spatial information into the membership function for clustering was proposed by Chuang *et al*. [14] to reduce the spurious blobs and remove the noisy spots in the images. An adaptive weighted averaging FCM (AWA-FCM) in which the spatial influance of the neighbouring pixels on the central pixel is included, was developed by Kang *et al.* [15]. To enhances the smoothness towards piecewise-homogeneous segmentation and reduces the edge blurring effect, Wang et al. [16] proposed adaptive spatial information-theoretic clustering (ASIC) algorithm which is obtained by incorporating spatial constrains to FCM. Ahmed *et al.* [17] proposed a spatial FCM algorithm named FCM_S, in which the objective function of the traditional FCM has been modified by introducing a regularization term to allow the labelling of a pixel to be influenced by the labels in its immediate neighbourhood. Chen *et al.* propose in [18] an improved version of FCM_S by introducing extra mean-filtered image algorithm (FCM_S1) and median-filtered image algorithm (FCM_S2) to replace the neighborhood term of FCM_S. In [19], this regularisation term is incorporated into a kernel based fuzzy clustering algorithm. In [20] authors incorporated spatial information to the clustering process using a novel metric of dissimilarity which is a combination of the feature dissimilarity and the spatial dissimilarity. In [21], Li *et al.* combine fuzzy c-means clustering algorithm with spatial constrains based on Markov random field (NGFCM). In [22] a generalized fuzzy c-means algorithm for fast and robust image segmentation has been proposed. In [23] Zhaon *et al.* introduces a novel non local adaptive spatial constraint term to modify the objective function of FCM. The adaptive spatial parameter for each pixel is designed to make the non local spatial information of each pixel playing a different role in guiding the noisy image segmentation. Segmentation experiments on synthetic and real images, especially magnetic resonance (MR) images, show that the proposed method is robust to noise in the image assess the performance of the proposed approach. In [24] authors present a new fuzzy c-means cluster segmentation algorithm based on modified membership that incorporates spatial information into the membership function for clustering. The spatial function is the weighted summation of the membership function in the neighborhood of each pixel under consideration. The proposed algorithm is initialized by the fast fuzzy c-means algorithm based on statistical histogram which speeds up its convergence.

The above methods greatly reduce the effect of noise and biased the FCM algorithm toward homogeneous clustering. However, as an iterative optimization algorithm, FCM has a strong chance to be trapped into local minima [4, 8]. For solving this weakness, recently evolutionary algorithms have been successfully applied. With this issue, we find the Ant Colony Optimization ACO [25], Particle Swarm Optimization (PSO) [26-30], Differential Evolution algorithm [31-33] and Artificial Bee Colony (ABC) algorithm [34-36].

The aim of this study is to propose a new segmentation method based on FCM clustering. Our method deals with two problems of the conventional FCM clustering algorithm. First, we consider spatial constrains during the clustering process by incorporating local neighbourhood information to the membership function. The local information reflects the spatial influence of the neighbouring pixels on the central pixel. Secondly, In order to avoid local minima of the spatial FCM algorithm, we use the ABC algorithm. The proposed method (ABC-SFCM) deals better with noisy images and improves global convergence due to the global searching of the ABC. Experimental results with synthetic and real images show that ABC-SFCM gives better performance than the conventional FCM, FCM_S1, FCM_S2, NGFCM algorithms and our SFCM algorithm without the hybridization of ABC algorithm.

The rest of this paper is organized as follows. In section 2, a description of the proposed Spatial FCM algorithm is presented. The application of ABC to the Spatial fuzzy clustering is given in section 3. In section 4, some computational experiments are given to show the performance and effectiveness of the proposed method in noise image segmentation. Finally, some conclusions are drawn in section 5.

2. THE SPATIAL FUZZY C-MEANS ALGORITM

2.1. The FCM algorithm

The fuzzy c-means (FCM) clustering algorithm which was first developed by Dunn [37] and later improved by Bezdek [2] is one of the most used methods in image segmentation. The algorithm is an iterative clustering process, which tends to produce an optimal *c* partition by minimizing the cost function defined as follows:

$$J_{FCM}(U,V) = \sum_{k=1}^{n}\sum_{i=1}^{c} u_{ik}^{m} d^{2}(x_k, v_i) \tag{1}$$

where $X = \{x_1, x_2, ...x_n\}$ is the data set in the *p*-dimensional vector space, *n* is the number of data items, *c* is the number of clusters with $2 \le c < n$, $u_{ik} = u_i(x_k)$ represents the membership of the k^{th} pixel to the i^{th} cluster, the parameter *m* is the degree of the fuzziness of the clustering process, v_i is the prototype of the center of cluster *i*, $d^2(x_k, v_i)$ is a distance measure of similarity between the k^{th} data item and cluster center v_i.

The membership function and cluster centers are defined by Equation (2) and (3) respectively in the process of iterations

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/(m-1)}} \qquad 2)$$

and

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m} \qquad 3)$$

Starting from a random partition, the FCM algorithm converges to a clustering solution by searching for local minima of the cost function. The algorithm stops when the membership function in two successive iterations does not change or when a maximum number of iterations is reached.

A fuzzy clustering problem is an optimization problem [22] as well as a combinatorial optimization problem that is hard to solve, even for small values of *c* and *n*.

2.2. The Spatial FCM algorithm

In the standard FCM algorithm for a pixel $x_k \in I$ where *I* is the image, the clustering of x_k with cluster *i* depends only on the distance measure between x_k and the center of the cluster *i*. Since the clustering process is related only to the histogram of image and does not take into account any spatial information, the FCM algorithm is sensitive to noise and other artefacts [9, 26].

One of the important characteristics of real-world images is that neighboring pixels usually have strong correlation between them. In other words, if the pixel x_k belongs to the cluster *i*, then its neighbors that exist in a window around it should have similar and high membership values in i^{th} clustering. Therefore, we propose in this paper, a new spatial FCM algorithm called SFCM to improve the performance and over-come the limitation of the standard FCM algorithm. In SFCM algorithm, a new membership function for clustering is used based on the spatial neighborhood information.

Our clustering algorithm takes into account the local spatial correlation between adjacent pixels by introducing the spatial information into the membership function of the conventional FCM algorithm. The fuzzy membership function given in equation (2) and the clusters centers given in equation (3) can be extended to:

$$u_{ik}^* = \frac{\sum_{j \in N_k} u_{ij} p_{kj}}{\sum_{s=1}^{C} \sum_{j \in N_k} u_{sj} p_{kj}} \qquad (4)$$

$$v_i^* = \frac{\sum_{k=1}^{n} u^{*m}_{ik} x_k}{\sum_{k=1}^{n} u^{*m}_{ik}} \qquad (5)$$

where u_{ik} is the membership function defined in the standard FCM. The probability p_{kj} exploits the spatial information and represents the influence of the neighbouring pixels on the central pixel x_k . N_k stands for the set of neighbors falling into a window around the central pixel x_k .

Based on the fact that the similar nearest neighbour is, the higher the interaction becomes and so the stronger the influence will be, the factor p_{kj} of the neighbor x_j is based on two factors: the pixels intensity or feature attraction d_{kj}^f and the spatial positions of the neighbors or distance attraction d_{kj}^s.

The feature attraction d_{kj}^f is defined as the absolute intensity difference between the pixel and its neighbors and it is defined as following:

$$d_{kj}^{f} = \left| x_k - x_j \right|$$

6)

And the distance attraction d_{kj}^{s} is defined as the Euclidean distance between the coordinates of the pixel and its neighbors as follows:

$$d_{kj}^{s} = \left\| k - j \right\|^2$$

7)

Then the contribution factor p_{kj} is defined as follows:

$$p_{kj} = \frac{1}{d_{kj}^{f} / \sigma_k^2} \times \frac{1}{d_{kj}^{s}}$$

8)

where σ_k^2 represents the local density surrounding the central pixel x_k .

With this definition, the probability p_{kj} increases when the grey level of the nearest j^{th} neighbours is close to the grey level of the central pixel x_k and vice versa.

The new cost function of the proposed SFCM algorithm is expressed as follows:

$$J_{FCM}^{*} \left(U^*, V\right) = \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik}^{*m} d^2 \left(x_k, v_i\right) \quad (9)$$

3. THE ABC BASED SFCM ALGORITHM

3.1 ARTIFICIAL BEE ALGORITHM

The Artificial Bee Colony (ABC) algorithm [38] is a relatively new global optimization algorithm developed by Karaboga in 2005. ABC algorithm takes its inspiration from the foraging behavior of honey bees (Karaboga, 2005). Since its introduction, the ABC algorithm has been applied with a great success to different optimization problems [39].

In the ABC algorithm, each food source position represents a solution to a specific problem and the amount of nectar in a food source represents the objective function (the fitness) of the solution. In the hive, three types of bees are considered: employed bees, onlooker bees and scout bees. The number of employed or onlooker bees is generally equal to the number of solutions in the population of solutions. The ABC algorithm consists of a number of cycles. During each cycle, there are three main parts: sending the employed bees to the food sources and measuring their nectar quantities; selecting the food sources by the onlookers; determining the scout bees and exploring new possible food sources.

Firstly, the ABC algorithm generates randomly an initial population of *Np* solutions. Each solution is a *D* dimensional vector, where *D* is the number of optimization parameters.

For generating an initial solution for the *ith* employed bee, the equation 10 is used

$$x_{ij} = x_{\min}^{j} + rand\,(0,\,1)\text{ x }(x_{\max}^{j} - x_{\min}^{j}) \quad (10)$$
$$(i = 1,...., Np \text{ and } j = 1,...., D)$$

where the $x_{\min}^{j}$ and $x_{\max}^{j}$ are the upper bound and upper bound of the *jth* component of the solution $z_{i,j}$.

After this initialization step, each employed bee searches the neighborhood of the food source (solution) in her memory and modifies it using equation (11)

$$u_{ij} = x_{ij} + \varphi_{ij} * (v_{ij} - x_{kj})$$
$$(i, k = 1,...., Np, \text{ i} \neq \text{k and } j = 1,...., D) \quad (11)$$

The employed bee updates her memory with this new solution if its quality is better; otherwise, it keeps the old solution and increments its trail by 1 (the solution has not be improved).

When all employed bees have terminated the search process, they share their experiences with the onlookers. Each onlooker bee is send to the food source (solution) with a probability p_i using the following equation:

$$p_i = \frac{fit_i}{\sum_{k=1}^{Np} fit_k} \quad (i = 1,....,Np) \tag{12}$$

After choosing a source, the onlooker bee produced a candidate food position from the old one in her memory, using equation 11. Just as employed bee does, the onlooker bee evaluates the new solution and compares its fitness with the one of the solution in her memory. If the new food source has equal or better quality than the old source, the old one is replaced by the new one. Otherwise, the old one is retained and the corresponding trail is increases by 1.

When all onlooker bees have update solutions, the solution with the maximum value of trail is recorded. If the trail of this solution exceeded a predetermined *limit*, the solution is considered to be an abandoned solution; meanwhile, the employed bee becomes a scout. The scout randomly produces a new solution by equation (10) and then compares the fitness of new solution with that of its old one. If the new solution is better than the old solution, it is replaced with the old one and set its own $trail_i$ into 0. This scout will be changed into an employed bee.

This process is repeated until the maximum number of cycles *MCN* is reached. The optimal solution is represented by the bee (solution) with the higher fitness value.

3.2. The ABC-SFCM algorithm

Owing to the advantages of the local spatial information, our new spatial fuzzy clustering algorithm (SFCM) improves the performance of the segmentation result of the noisy image. But since it is an iterative hill-climbing algorithm, it can be trapped in the local minimum. In order to avoid the local convergence, we consider in this paper the clustering image segmentation as an optimization problem and we use the global searching ability of the ABC algorithm to search the optimum cluster centers.

In the proposed clustering algorithm (ABC-SFCM), a swarm of *Np* bees represents a set of cluster centers. We formulate each bee as a potential solution to the fuzzy clustering problem. Each individual bee z_i in generation *G* is formulated as $z_i = \{v_{i1}, v_{i2}, ...v_{ic}\}$ where v_{ik} represents the k^{th} cluster center for the i^{th} bee. The bee's quality is measured using the objective function:

$$fit_i = \frac{1}{1 + J_i^*(U^*, V)} \tag{13}$$

with

$$J_i^*(U^*, V) = \sum_{j=1}^{c} \sum_{k=1}^{n} u{*}_{jk}^{m} \left\| x_k - v_{ij}^* \right\|^2 \tag{14}$$

The smaller is J_i^*, the higher is the individual fitness fit_i and the better is the clustering result.

When algorithm gets into the convergence, we convert the optimal fuzzy partition matrix to a crisp partition matrix. The defuzzifcation is carried out by assigning each pixel to the cluster with the highest membership.

The main steps of ABC-SFCM algorithm are presented bellow:

1. Initialize the cluster number *c* and all the constant parameters;
2. Generate initial population using equation (10)
3. Evaluate the population using equation (13)
4. Set cycle to 1
5. FOR each employed bee
   a. Produce new solution by using equation (11)
   b. Calculate the fitness using equation (13);
   c. Apply the greedy selection process
6. End For
7. FOR each onlooker bee
   a. Select a solution using equation (12)
   b. Produce new solution using equation (11)
   c. Calculate the fitness using equation (13)
   d. Apply the greedy selection process
8. End For
9. If there is abandoned solution then
   a. Generate a random solution using equation (10)
10. Memorize the best solution (best cluster centers) achieved yet

11. Update cycle
12. If cycle <= *MCN* goto step 5
13. Do the segmentation by assigning each pixel to the cluster for which the membership value is higher.

4. COMPUTATIONAL EXPERIMENTS

In this section, the results of the application of the proposed ABC-SFCM algorithm in noisy image segmentation are presented. In our experiments, we use a number of synthetic and real images corrupted respectively by "Gaussian" and "salt & pepper" noises to test the robustness of the proposed algorithm.

Besides our ABC-SFCM algorithm, five other segmentation methods are also used in the comparative experiments. The first one is the conventional FCM algorithm proposed by Bezdek [3]. The second and the third ones are the Spatial fuzzy clustering algorithms FCM_S1 and FCM_S2 proposed by Chen *et al.* [18], the fourth one is the NGFCM algorithm proposed by Xiaohe *et al.* [21]. The last one is our Spatial FCM algorithm described in section 2.

In all experiments, the parameter α in FCM_S1 and FCM_S2 is set to be 0.6 and the parameter β in NGFCM is set to 1950 in consideration to the compromise between computational cost and segmentation accuracy. There are three control parameters in ABC algorithm, the swarm size *Np*, the maximum cycle number *MCN* and the limit. They are set as follow: *Np*=20, *MCN*=2000, *limit*=100.The weighting exponent *m* is set to 2. All the algorithms have been developed with Borland C++ on a Pentium IV, 1.7 GHz PC, with 512 KB cache and 2 GB of main memory with Windows XP environment.

4.1. Results on synthetic image with 3x3 local window

To verify the ability of the algorithm to resist the impact of noise, we apply the six algorithms first to a synthetic image shown in Figure 1. The synthetic image is composed of 126x126 pixels, including two clusters whose gray levels are 0 and 90 (cf Figure 1(a). Each cluster is corrupted by a "Gaussian" noise in Figure 1 (b) and a "Salt & Pepper" noise in Figure 2(b). A 3*3 window centred on each pixel except the central pixel itself is used for each noisy image.

Figure 1 and Figure 2 are the segmentation results on a corrupted image with "Gaussian" noise and "Salt&Pepper" noise. Visually it can be seen that the traditional FCM is much more sensitive to noise, and the segmentation is far from the ideal because it does not take into account the spatial local information. FCM_S1, FCM_S2, NGFCM and SFCM give better results because of the neighborhood information used in the clustering process. SFCM performs noise image segmentation much better than FCM_S1, FCM_S2 and NGFCM and its segmentation result is much closer to the ground truth. ABC-SFCM outperforms others algorithms because it uses the global searching ability of the ABC algorithm and the optimal cluster centers can be obtained much better.

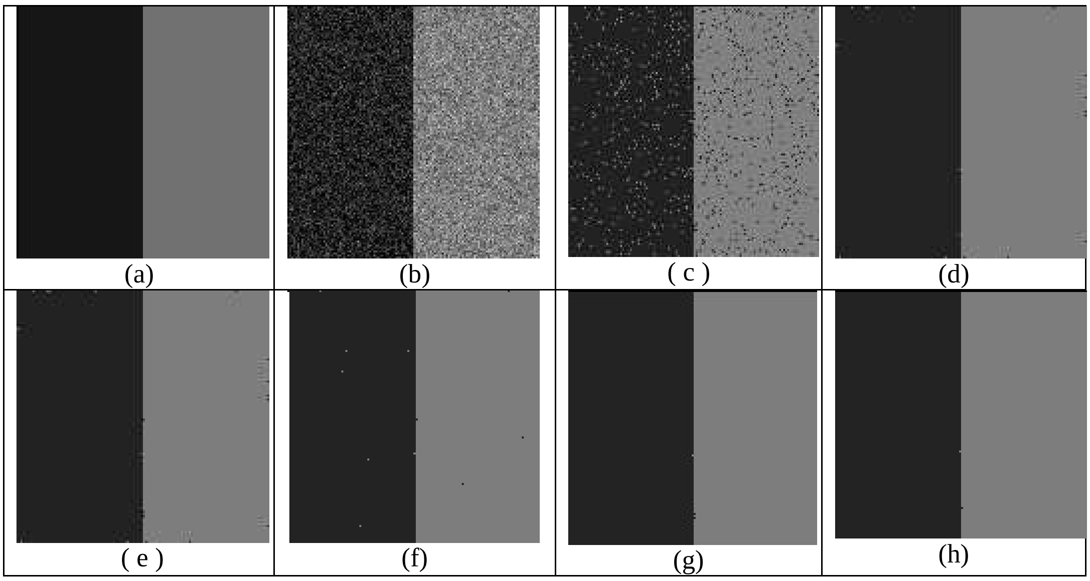

Figure1. Comparison of segmentation results on a two-clusters synthetic image corrupted with Gaussian noise. a) Original image. b) Noisy image with 5% Gaussian noise. c) Result by FCM. d) Result by FCM_S1. e) Result by FCM_S2. f) Result by NGFCM. g) Result by SFCM. h) Result by ABC-SFCM.

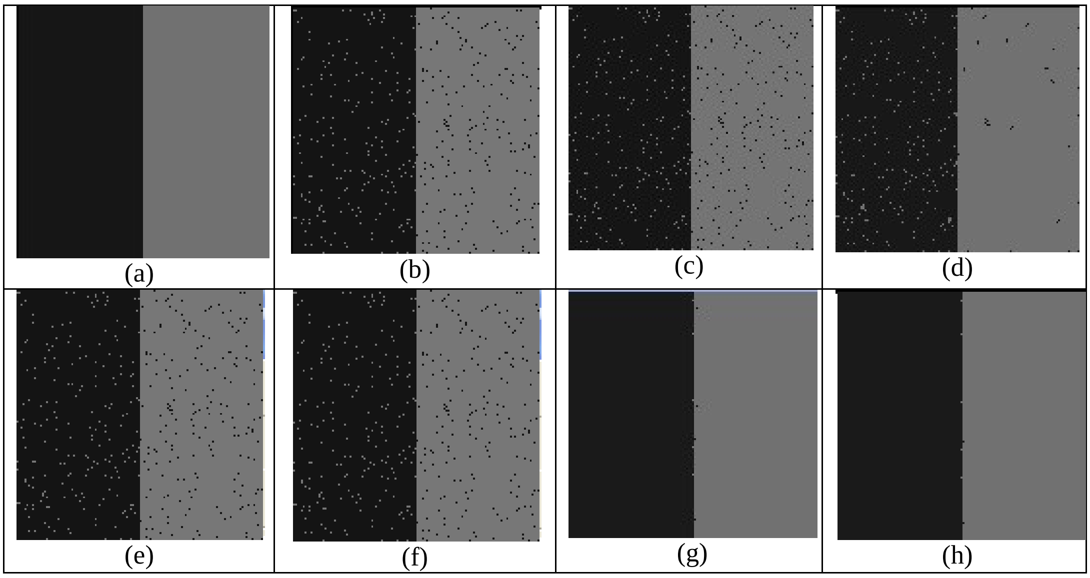

Figure 2. Comparison of segmentation results on a two-clusterss synthetic image corrupted with Salt&Pepper noise. (a) original image. (b) noisy image with 5% ‘Salt & pepper’ noise. (c)Result by FCM. (d)Result by FCM_S1. (e)Result by FCM_S2. (f)Result by NGFCM. (g)Result by SFCM. (h)Result by ABC-SFCM.

The segmentation accuracy of applying these algorithms to the synthetic image corrupted respectively by the “Gaussian” noise and the “Salt and pepper” noise with different levels is given in Table 1.

Here, the Segmentation Accuracy [1] (SA) is defined as:

$$SA = \frac{\text{Number of correctly classified pixels}}{\text{Total number of pixels}} x\, 100\% \tag{15}$$

From Table1, we can see that the proposed ABC-SFCM algorithm gives better performance than FCM_S1 and FCM_S2, NGFCM and SFCM algorithms in the presence of “Gaussian” and ”Salt & pepper” noises. This performance is due to the introduction of local spatial information and the use of the ABC algorithm which performs a global search rather than a local search in the other algorithms.

Table1. SA% of the clustering algorithms on synthetic image

Noise	FCM	FCM_S1	FCM_S2	NGFCM	SFCM	ABC-SFCM
Gaussian with 3%	97.96	99.77	99.79	99.93	99.96	99.98
Gaussian with 5%	95.49	99.68	99.88	99.92	99.95	99.96
Gaussian with 7%	94.20	98.83	99.28	99.90	99.91	99.93
Salt & pepper 5%	97.53	98.48	98.67	97.53	99.91	99.93
Salt & pepper 10%	95.01	96.48	97.31	98.89	99.79	99.82
Salt & pepper 15%	92.61	94.24	93.04	95.79	99.50	99.53

4.2. Results on real images corrupted by noises

In this section, we will examine the experimental results of application ABC-SFCM algorithm on real images perturbed with “Gaussian” noise with different levels.

4.2.1. Results on eight corrupted by Gaussian noise with 5x5 local window

We apply the six algorithms on a real- world standard test image *eight* corrupted with “Gaussian” noise (cf Figure. 3(a)) in order to examine the algorithms’ robustness in the presence of noise. In this study, the class number c is set to be 2. The results of segmentation by applying the six clustering algorithms to the image are presented in Figures. 3(b-f). Visually, FCM is affected by the noise while FCM_S, FCM_S2, NGFCM, SFCM and ABC-SFCM remove the noise. The proposed method performs the best segmentation with more homogenous regions and with least spurious components.

The quality of the fuzzy clustering obtained from the different algorithms on *eigth* image is formally evaluated using the concept of uniformity as presented in [40] and Xie-Beni validity index [41-42].

The uniformity of a segmentation result is defined by:

$$U = 1 - \frac{\sum_{i=1}^{c} \sigma_i^2}{\sigma^2} \tag{16}$$

where c is the number of classes, σ_i^2 is the within-cluster variance of the i^{th} cluster, and σ^2 denotes the total variance of the image. A high uniformity value will reflects a better segmentation result.

Xie-Beni validity index is defined by [41, 42]

$$V_{xb} = \frac{\sum_{i=1}^{c}\sum_{j=1}^{N} u_{ij}^2 \left\| x_j - v_i \right\|^2}{N \times \min_{i \neq j} \left\| v_i - v_j \right\|^2} \tag{18}$$

where x_j denotes the grey level of the j^{th} pixel, v_k is the center of the k^{th} cluster; $\left\| x_i - v_k \right\|$ is the Euclidean distance between the i^{th} pixel and the center of the k^{th} cluster. c stands for the number of clusters and N stands for the number of pixels.

A small value of V_{xb} indicates that the clusters obtained are compacts and well separated.

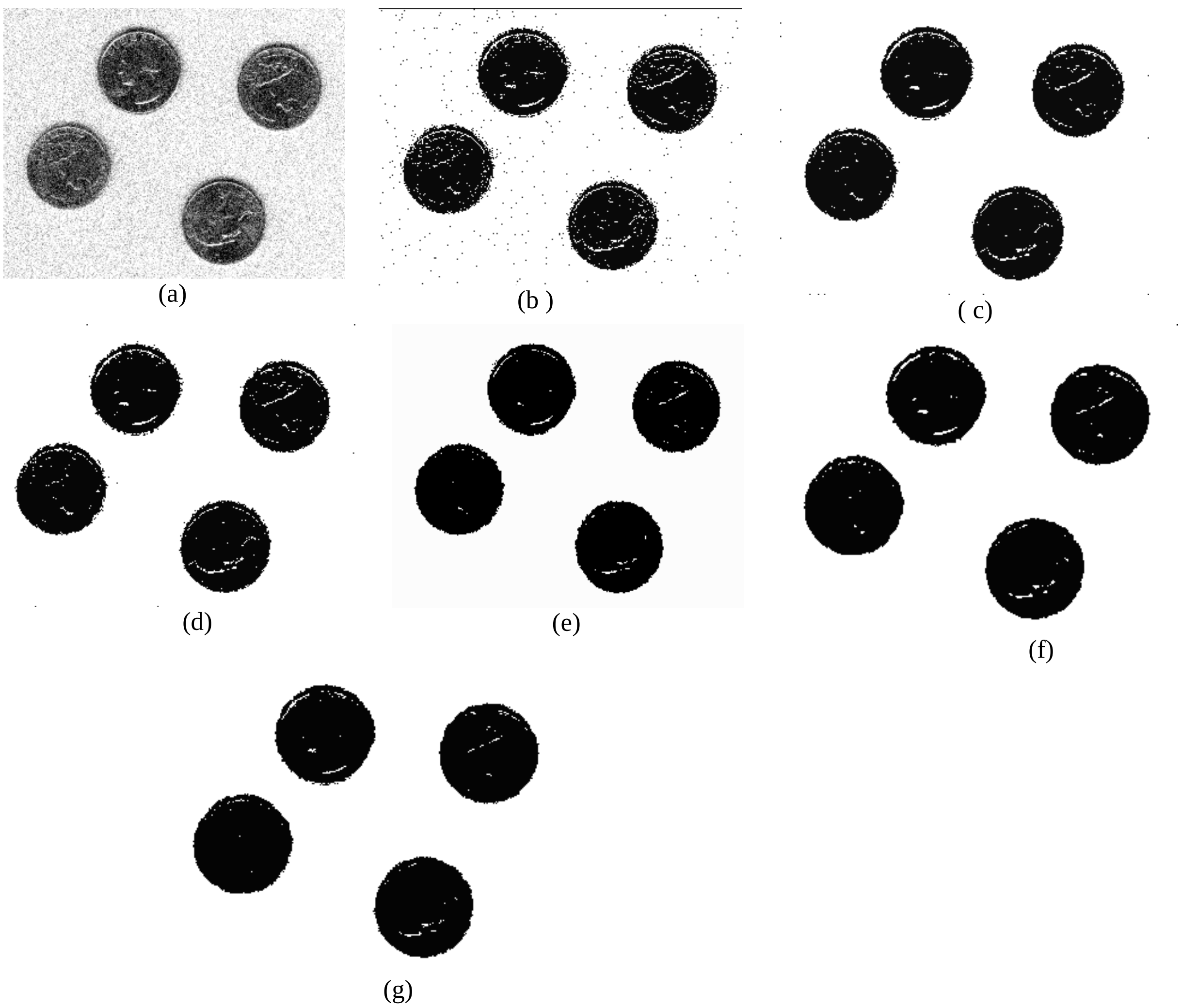

Figure 3. Comparison of segmentation results on eigth image. (a) Noisy image with 7% 'Gaussian' noise. (b) Result by FCM. (c) Result by FCM_S1. (d) Result by FCM_S2. (e) Result by NGFCM. (f) Result by SFCM. (g) Result by ABC-SFCM.

The most dominant results of the algorithms over 20 different run trials are presented in Table2. From Table 2, it can easily seen that ABC-SFCM algorithm is less sensitive to noise and outperforms others algorithms for the test image.

Table2. values of Uniformity value and Xie-Beni validity index of the clustering algorithms on eigth image

	FCM	FCM_S1	FCM_S2	NGFCM	SFCM	ABC-SFCM
Uniformity	0.450	0.530	0.533	0.535	0.537	0.539
V_{xb}	0.060	0.054	0.044	0.040	0.038	0.036

4.2.2. Results on Brain image with 5x5x local window

Figure. 4(a) is a simulated magnetic resonance (MR) brain image available on the site Brainweb: http://www.bic.mni.mcgill.ca/brainweb/. This brain image was simulated with 5% noise and no intensity inhomogeneity. The number of clusters was assumed to be 4, corresponding to gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and background (BKG). Figures. 4(b-g) show the segmentation results of FCM, FCM_S1, FCM_S2 , NGFCM, SFCM and ABC-SFCM respectively.

From Figure 4, we can see that our method result is much better and closer to the ground truth that others algorithms. This performance is attributing to the introduction of the spatial information to the membership function and to use of the global search to ABC algorithm.

To validate the accuracy and reliability of each segmentation method, compared with the ground truth of Brain image, we computed the Jaccard similarity [43]. The Jaccard similarity measures the similarity of two sets as the ration of the size of their intersection divided by the size of their union. Let V_g^k and V_s^k denotes the total number of pixels labeled into a cluster k in the ground truth (g) and the obtained segmentation (*s)*. For cluster k the Jaccard similarity $J^k(g,s)$ is defined by :

$$J^k(g,s) = \frac{\left|V_g^k \cap V_s^k\right|}{\left|V_g^k \cup V_s^k\right|} \qquad (19)$$

A good segmentation is obtained when $J^k(g,s)$ is near 1 which means that the cluster k is well detected.

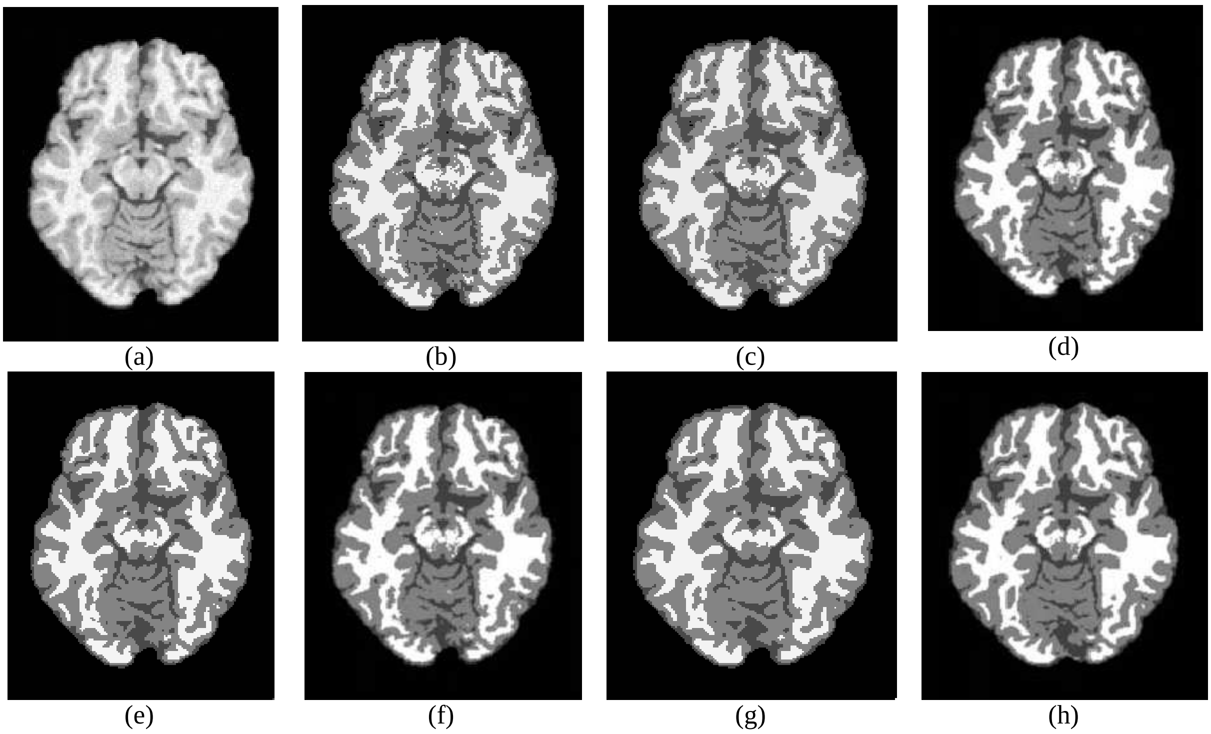

Figure 4. Comparison of segmentation results on Brain image. (a)The Brain image corrupted with 5%noise and no intensity inhomogeneity. (b) FCM result. (c) FCM_S1 result. (d) FCM_S2 result. (e) NGFCM result (f) SFCM result. (g) ABC-SFCM result. (h) ground truth.

Table 3 quantitatively compare the classification results obtained from the different clustering algorithms for Figure 5 containing 3%, 5% and 7% noise with non intensity inhomogeneity. From Table 3, ABC-SFCM outperforms the other clustering algorithms.

Table 3. Jaccard similarity measure of different clustering methods on Brain phantom MR image with different levels of noise and no intensity inhomogeneity

Noise level	Method	CSF	GM	WM	BKG
3%	FCM	0,80	0,86	0,80	0,92
	FCM_S1	0,84	0,89	0,88	0,95
	FCM_S2	0,87	0,92	0,90	0,96
	NGFCM	0,90	0,94	0,91	0,96
	SFCM	0,90	0,94	0,90	0,96
	ABC-SFCM	0,91	0,95	0,90	0,97
5%	FCM	0,73	0,85	0,75	0,91
	FCM_S1	0,77	0,88	0,89	0,94
	FCM_S2	0,82	0,89	0,90	0,96
	NGFCM	0,81	0,9	0,90	0,96
	SFCM	0,83	0,91	0,91	0,96
	ABC-SFCM	0,84	0,90	0,92	0,97
7%	FCM	0,68	0,79	0,70	0,80
	FCM_S1	0,72	0,88	0,80	0,93
	FCM_S2	0,77	0,88	0,82	0,94
	NGFCM	0,78	0,89	0,84	0,942
	SFCM	0,79	0,90	0,86	0,942
	ABC-SFCM	0,79	0,90	0,86	0,946

5. CONCLUSION

This paper introduced a new spatial fuzzy clustering algorithm optimised by the ABC algorithm. ABC-SFCM has two principles characteristics: first it performs better noise image segmentation by making use of the spatial local information into the membership function. Secondly, it uses the global search capability of ABC algorithm to deal with the premature convergence of the FCM algorithm. Experiments with synthetic and real images show that ABC-SFCM is better compared to others spatial fuzzy clustering methods.

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