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Fuzzy Artificial Bee Colony System with Cooling Schedule for the Segmentation of Medical Images by Using of Spatial Information

Jzau-Sheng Lin and Shou-Hung Wu
National Chin-Yi University of Technology, Taichung, Taiwan

Abstract: In this study, segmentation of medical images using a fuzzy artificial bee colony algorithm with a cooling schedule is created. In this study, we embed ed fuzzy inference strategy into the artificial bee colony system to construct a segmentation system named Fuzzy Artificial Bee Colony System (FABCS). A conventional FCM algorithm did not utilize the spatial information in the image. We set a local circular area with a variable radius by using a cooling schedule for each bee to search suitable cluster centers with the FCM algorithm in an image. The cluster centers can be calculated by each bee with the membership states in the FABCS and then updated iteratively for all bees in order to find near-global solution in MR image segmentation. The proposed FABCS found the cluster centers with local spatial information in stead of global pixels' intensities. In the simulation and real medical-image segmentation results, the proposed FABCS network can reserve the segmentation performance.

Keywords: Artificial bee colony system, FCM, medical image segmentation

INTRODUCTION

Magnetic Resonance Imaging (MRI) is the preferred imaging modality for examining many neurological conditions which alter the shape, volume and distribution of brain tissue. Reliable measurement can be performed by using image segmentation for these alterations. Several approaches (Lin, 2001; Yang *et al*., 2002; Wang *et al*., 2004; Ahmed *et al*., 2002; Lyer *et al*., 2002) have been developed to automate such measurements by segmentation. However, some of these methods do not take advantage of the MRI images. The analysis of such medical images can be accomplished by using supervised or unsupervised classification methods. In supervised classification strategies, the Region of Interest (ROI) is defined by the associated human interaction and the approach trains on the ROI and flags each pixel in the scenes associated with a given signature. However, a supervised approach is very time-consuming for large volumes and heavy biases may be introduced by an unskilled technician. The unsupervised classification methods classify the target data sets without the aid of training sets, but a post-processing step is required to correct misclassified pixels.

The fuzzy clusters are generated by dividing the training samples in accordance with the membership function. The Fuzzy C-Means (FCM) (Wang *et al*., 2004; Ahmed *et al*., 2002; Lyer *et al*., 2002) algorithm used the memberships of a training sample across clusters that sum up to 1, which means the different grades of a training sample are shared by distinct clusters. Membership state is important for the correct feature of data substructure in clustering problem. If a training sample has been classified to a suitable cluster, then membership is a better constraint for which the training sample is closest to this cluster. In this study, we embedded the FCM strategy into an artificial bee colony to construct the FABCS and used to the application of medical MRI images segmentation.

Swarm intelligence is an interesting research field that models the population of interacting agents or swarms that can be able to organize by themselves. Swarm intelligence systems are popular in the natural world such as immune system, ant colony, a flock of birds or bacterial foraging. Artificial bee colony algorithm, an optimization strategy based on the intelligent behavior of honey bee swarm, is one of the swarm intelligence systems.

Artificial Bee Colony (ABC) algorithm was proposed by Karaboga, (2005), Basturk and Karaboga (2006), Karaboga and Basturk, (2007) and Karaboga and Basturk 2007) for optimizing numerical problems. The algorithm simulates the intelligent foraging behavior of honey bee swarms. It is a robust stochastic optimization algorithm. Several well-known heuristic strategies such as Genetic Algorithm (GA) (Dey *et al*., 2010), Differential Evolution (DE) (Paterlini and Krink, 2006), Particle Swarm Optimization (PSO) (Omran *et al*., 2005; Lin *et al*., 2009) on constrained and unconstrained problems were proposed to compare the performance with the ABC algorithm.

On an image, the pixels are highly correlated one another. That is the pixels in the neighborhood own nearly the same feature data. Therefore, the spatial relationship of neighboring pixels is an important characteristic that

Corresponding Author: Jzau-Sheng Lin, National Chin-Yi University of Technology, Taichung, Taiwan

can be of great aid in imaging segmentation. In this study, we randomly put several bees into an image to find cluster centers on a local circular area with a fixed radius by using of FCM algorithm with a cooling schedule to decrease the searching radius iteratively. Then we select the suitable cluster centers iteratively with the bees' searching strategy till the terminal condition is met. The purpose of selecting local area is to reserve the local feature data to segment an image effectively.

METHODOLOGY

Clustering techniques: Clustering techniques are the process of recognizing clusters in testing samples based on some similarity measures. Distance measurement is generally used for evaluating similarities between training data. Hard C-Means (HCM) is the simplest and most commonly used clustering method. It represents each cluster by the mean value of the data points within the cluster. In a target space, given n objects, the HCM allocate each object to one of C clusters and minimize the sum of squared Euclidean distances between each object and the center of the cluster belonging to every such allocated object. The object function of HCM is defined as Eq. (1):

$$J_{HCM} = \frac{1}{2}\sum_{x=1}^{n}\sum_{i=1}^{c}\left\|z_x^i - \varpi_i\right\|^2 \tag{1}$$

where, z^i_x is the xth data point belonging to the ith cluster, ϖ_i is the cluster center of the ith cluster, c is the number of clusters and n is the number of data points in cluster i.

First, the HCM takes c randomly selected pixels and makes them the initial centers of the c clusters being formed. And, this algorithm assigns each pixel to the cluster with $c$entre closest to it. Then, the centers of the c clusters are recalculated and the pixels are redistributed. This step is repeated for a specified number of iterations or until there is no change to the membership of the clusters over two successive iterations. It is known that the HCM algorithm maybe trap at local optimal solutions, depending on the choice of the initial cluster centers.

The theory of fuzzy logic provides a mathematical environment to capture the uncertainties as the same human cognition processes. The fuzzy clusters are generated by dividing the training samples in accordance with the membership functions. A component in the membership matrix denotes the grade of membership that a training sample belongs to a cluster. Real data unavoidably involves some noises, either from interface due to noise sources which exist in the natural environment or from the equipment itself. Therefore, the drawback of FCM will be significant while processing improper data. The purpose of the FCM approaches, like the conventional clustering techniques, is to group data into clusters or similar items by minimizing a least-squared error measure. The FCM algorithms used the probabilistic constraint to enable the memberships of a training sample across clusters to sum up to 1, which means the different grades of a training sample are shared by distinct clusters. In contrast, each component generated by the FCM corresponds to a dense region in the data set. Each cluster is independent of the other clusters in the FCM strategy. The objective function of the FCM can be formulated as:

$$J_{FCM} = \frac{1}{2}\sum_{x=1}^{n}\sum_{i=1}^{c}\mu_{x,i}^{m}\left\|z_x - \varpi_i\right\|^2 \tag{2}$$

where, memberships and centroids are defined as:

$$\mu = \left(\sum_{l=1}^{c}\frac{\left(\left\|z_x - \varpi_i\right\|^2\right)^{1/(m-1)}}{\left(\left\|z_x - \varpi_l\right\|^2\right)^{1/(m-1)}}\right)^{-1}$$
$$x = 1, 2, \ldots, n,\ i = 1, 2, \ldots, c, \tag{3}$$

and

$$\varpi_i = \frac{1}{\sum_{y=1}^{n}(\mu_{y,i}^{m})}\sum_{x=1}^{n}(\mu_{y,i}^{m})z_x \tag{4}$$

The value m, so-called fuzzification parameter, would alleviate the noise effect when the centroids are computed. The larger the value of m, the greater will be the sensitivity to noise.

Artificial Bee Colony (ABC) algorithm: A colony of honey bees can extend itself over long distances in order to search food sources. The foraging process is begun in a colony by scout bees to search for plentiful flower patches. More bees visit flower patches with large amounts of pollen or nectar that can be collected with less effort, whereas patches with less pollen or nectar attract fewer bees. During the warm season, a colony continues its foraging process, keeping a percentage rate of the population as scout bees. When scout bees return to the hive, they found a patch rated above a certain quantity threshold deposit their nectar or pollen and go to the "dance floor" to perform a "waggle dance" dance. This special dance is essential for bees' communication in a colony and includes three kind of information regarded a flower patch: its distance from the hive, the direction in which it will be found and its quantity rating. These information help the colony to assign its bees to flower patches accurately, without any guide or map. This dance enables the colony to calculate the relative value of different patches according to both the quantity of the food they supply and the amount of energy needed to collect it. After waggle dancing on the dance floor, the scout bees go back to the flower patches with follower bees that were waiting inside the hive. More follower bees are assigned to more hopeful patches. This process allows the colony to collect food efficiently and quickly. While harvesting from a patch, the bees monitor their food level.

When bees return to the hive, it is necessary to decide the next waggle dance. If the patch is always good enough as a food source, it will be noticed waggle dance and more bees will be recruited to that source. The conventional ABC algorithm is described as:

- Load the training patterns
- Initialize the bees' population
- calculate the fitness of the population
- While (stopping condition is not met)
  //Forming new population
- Select sites for neighborhood search
- Recruit bees for selected sites (more bees for the best *e* sites) and evaluate fitness
- Select the fittest bee from each site
- Assign remaining bees to search randomly and evaluate their fitness
- End While

The proposed fuzzy artificial bee colony system: In an image, one of the important characteristics is that neighboring pixels are greatly correlated. In other words, similar feature values are possessed by these neighboring pixels. The spatial information is important in clustering problem, but it is not considered in a standard FCM algorithm.

In the proposed FABCS, the clustering is a two-pass process each iteration. In the first pass, the scout bees were randomly put in the space domain of a target image. And the spatial information are searched by using of the function of ABC. The second pass is the same as that in standard FCM to calculate the membership function in the spatial domain for each scout bee. Then, the local cluster process is stopped when the maximum difference between two cluster centers at two successive processes is less than a threshold. In order to find near-optimal solution efficiently, we embedded a cooling schedule to narrow the area iteratively for the candidate bees to recruit bees for the best sites and poor sites randomly. In this study, the decrement function shown as in Eq. (5) is used as cooling schedule.

$$r(t) = \frac{1}{\varepsilon + 1}\left[\varepsilon + \tanh(w)^t\right] r(t-1) \qquad (5)$$

where r is the radius of the searching circle for a candidate bee and w a small constant which closes to unit as well as ε is also a constant. Additionally, t is the iterations. (Lin 1999) showed that Eq. (5) can result in a faster decrement speed than that resulted from the conventional decrement functions. In Eq. (5), a suitable value of w can be set as $0.0 < w < 1.0$. A smaller value of w was selected; the convergent time can speed up but fall in a local minimum easily. The flowchart of the proposed FABCS algorithm is shown as in Fig. 1. After the convergence, defuzzification is applied to assign each pixel to a specific cluster for which the membership is maximal.

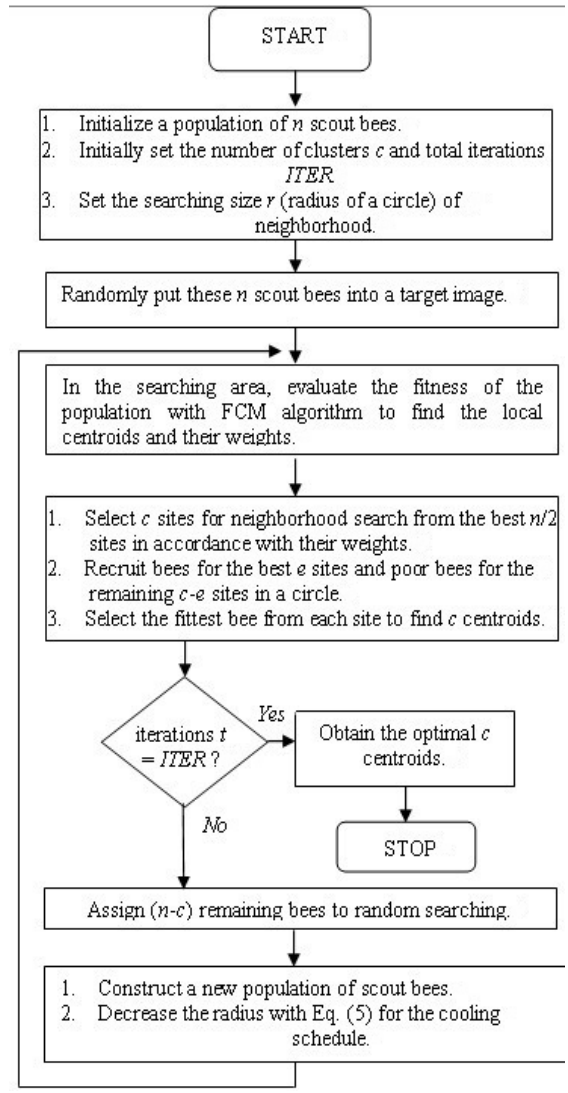


Fig. 1: The flowchart of the proposed FABCS algorithm

EXPERIMENTAL RESULTS

In order to show the performance, all simulations are executed with the interpreter language of MATLAB in a personal computer. The performances for two frequently-used methods i.e., the HCM and FCM and the proposed FABCS algorithm were first compared in the simulation study. And, the real medical images were segmented by the proposed FABCS algorithm.

Computer simulations: The computer generated image was made up of seven overlapping ellipses. Each ellipse represents one structural area of tissue. From the periphery to the center, they were the background (BKG, gray level = 30), skin or fat *(S/F*, gray level = 75), gray matter (GM, gray level = 120), white matter (WM, gray

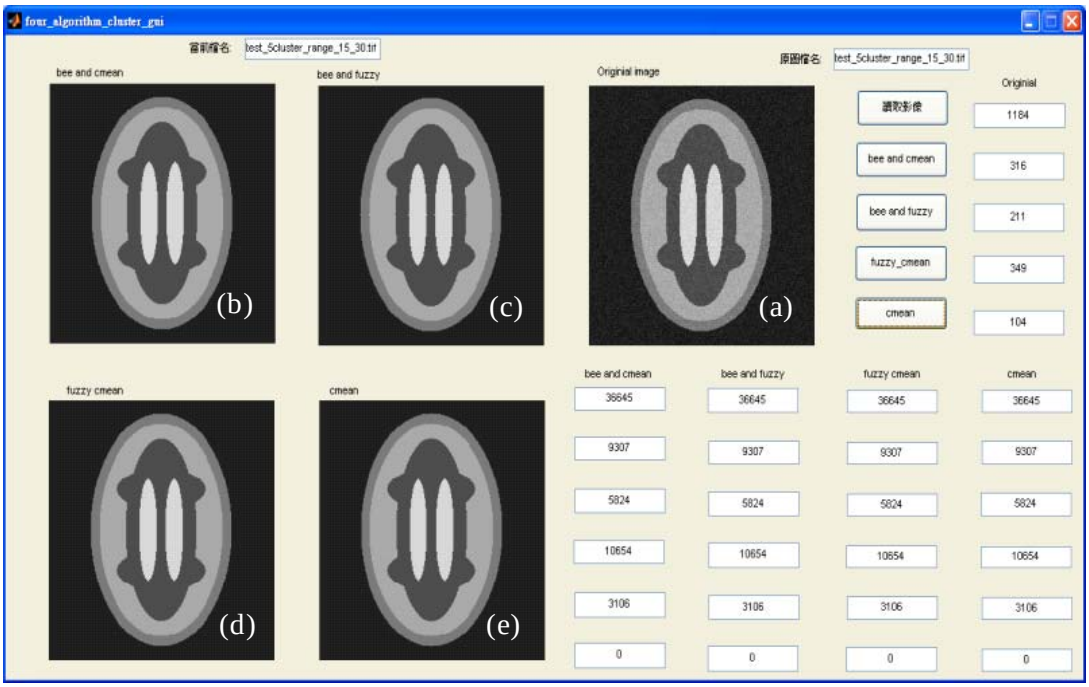


Fig. 2: The test phantom of four objects with added noise ($k \leq 15$) in (a) and the result images shown in (b), (c), (d) and (e) using the ABC+HCM, FABCS, FCM and HCM methods, respectively

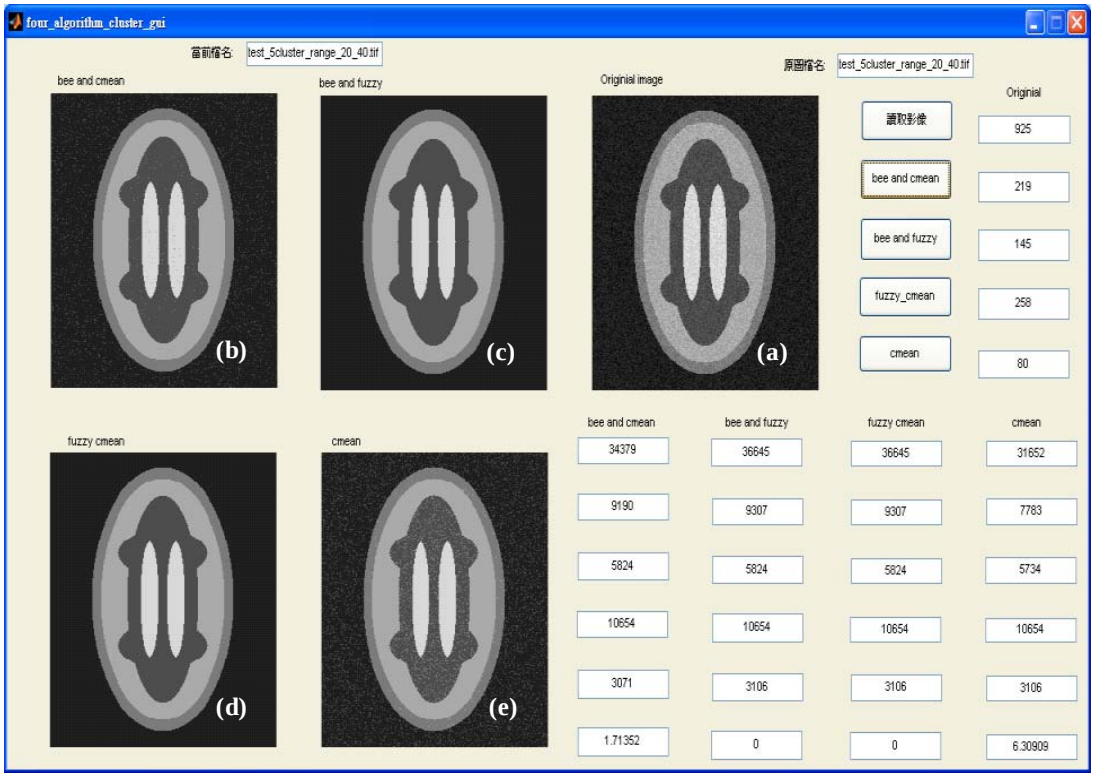


Fig. 3: The test phantom of four objects with added noise ($k \leq 20$) in (a) and the result images shown in (b), (c), (d) and (e) using the ABC+HCM, FABCS, FCM and HCM methods, respectively

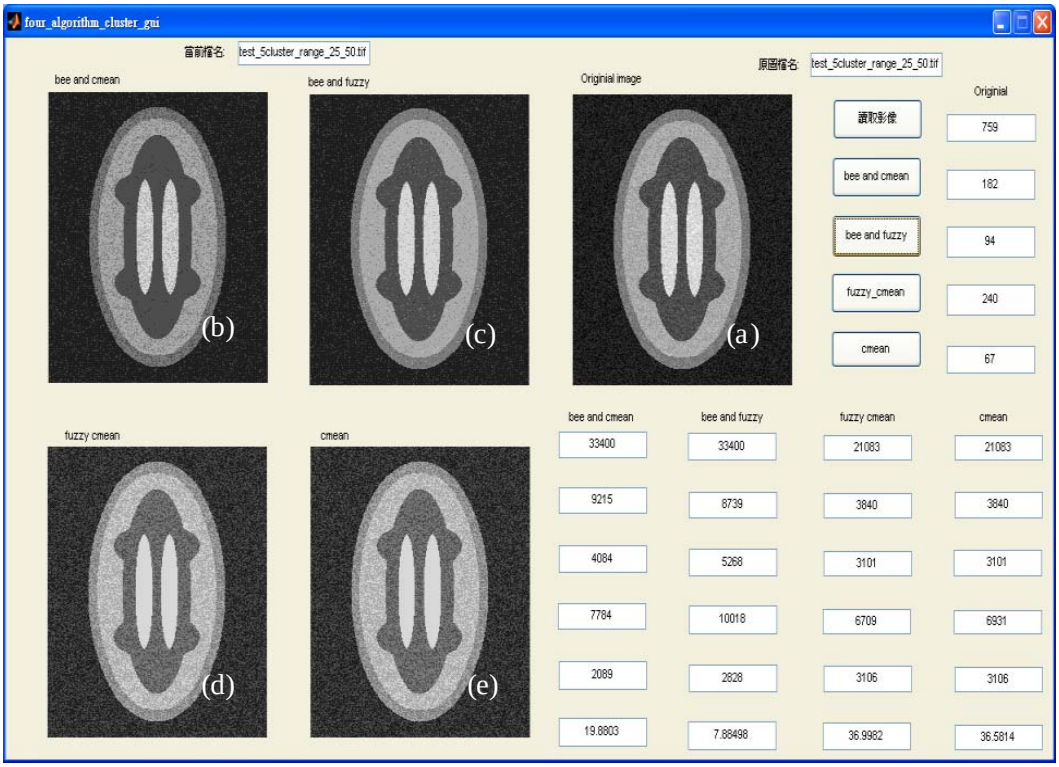


Fig. 4: The test phantom of four objects with added noise (k≤25) in (a) and the result images shown in (b), (c), (d) and (e) using the ABC+HCM, FABCS, FCM and HCM methods, respectively

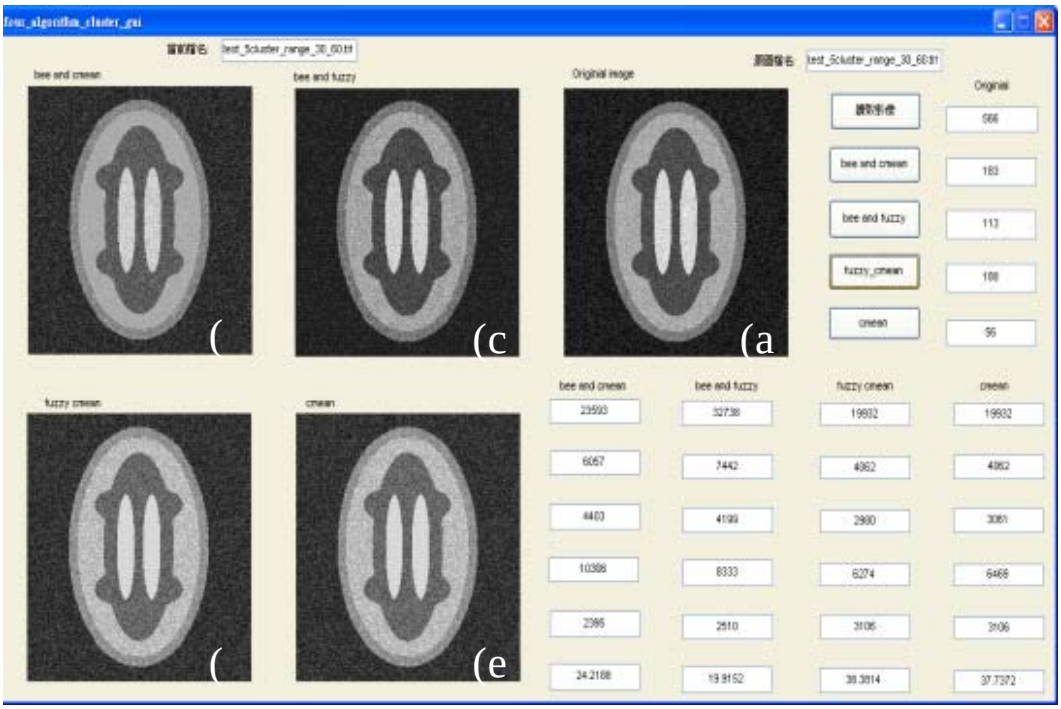


Fig. 5: The test phantom of four objects with added noise (k≤30) in (a) and the result images shown in (b), (c), (d) and (e) using the ABC+HCM, FABCS, FCM and HCM methods, respectively

Table 1: The segmentation performance for hcm, fcm, bee + hcm and the proposed fabcs algorithm using the test phantom with k< = 15

Simulate	Actual pixels	HCM	FCM	Bee + HCM	FABCS
Background	36645	36645	36645	36645	36645
S/F	9307	9307	9307	9307	9307
GM	5824	5824	5824	5824	5824
WM	10654	10654	10654	10654	10654
CSF	3106	3106	3106	3106	3106
Average error		0%	0%	0%	0%

Table 2: The segmentation performance for hcm, fcm, bee + hcm and the proposed fabcs algorithm using the test phantom with k< = 20

Simulate	Actual pixels	HCM	FCM	Bee + HCM	FABCS
Background	36645	31652	36645	34379	36645
S/F	9307	7783	9307	9190	9307
GM	5824	5734	5824	5824	5824
WM	10654	10654	10654	10654	10654
CSF	3106	3106	3106	3071	3106
Average error		6.31%	0%1.7	1%	0%

Table 3: The segmentation performance for hcm, fcm, bee + hcm and the proposed fabcs algorithm using the test phantom with k< = 25

Simulate	Actual pixels	HCM	FCM	Bee+HCM	FABCS
Background	36645	21083	21083	33400	33400
S/F	9307	3840	3840	9215	8739
GM	5824	3101	3101	4084	5268
WM	10654	6931	6709	7784	10018
CSF	3106	3106	3106	2089	2828
Average error3		6.58%	37.0%	19.88%	7.88%

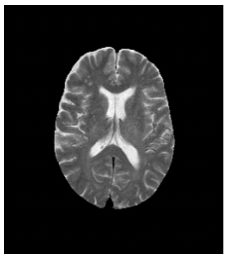
Table 4: The segmentation performance for hcm, fcm, bee + hcm and the proposed fabcs algorithm using the test phantom with k< = 30

Simulate	Actual pixels	HCM	FCM	Bee+HCM	FABCS
Background	36645	19932	19932	23593	32738
S/F	9307	4062	4062	6057	7442
GM	5824	3061	2980	4403	4199
WM	10654	6469	6274	10306	8333
CSF	3106	3106	3106	2395	2510
Average error		37.74%	38.38%	24.22%	19.92%

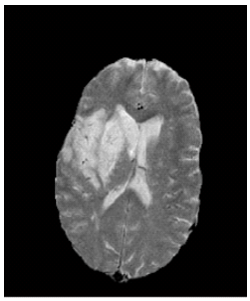
level = 165) and cerebrospinal fluid (CSF, gray level = 210), respectively. The gray levels for each region were set to a constant value. In addition, the noise of uniform distribution with the gray levels ranging from -*K* to *K* was then added to the simulated phantoms. The noise level *K* for different cases was set to be 15, 20, 25 and 30, respectively.

The segmented images for the test phantom are shown in Fig. 2-5. The accuracy for the four image segmentation methods described above are listed in Table 1-4. From these tables, they can easily be seen that all the methods would extract the objects very accurately for the noise levels $K = 15$ and 20, respectively. For larger noise levels of $K = 25$ and 30, the proposed FABCS algorithm would be more accurate in image segmentation than the other three methods. An average accuracy is 92.12% for $K = 25$ and 80.08% for $K = 30$ may be achieved using the FABCS approach.

Real MRI image segmentation: The second experiment showed the segmentation performance with medical images. These real medical images in Fig. 6 and 7 are acquired with T_2-weighted sequences. The acquisition parameters with different Repetition Time (*TR*) and Echo

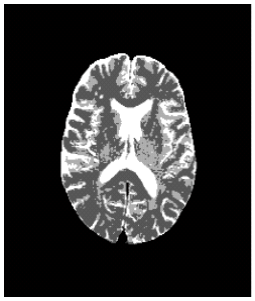


(a) Normal with *TR*/*TE* = 2500 ms/75 ms

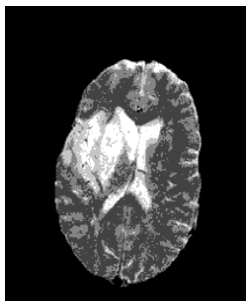


(b) Cerebral-infarction with*TR*/*TE* = 2500 ms/75 ms

Fig. 6: T_2-weighted brain images



(a)



(b)

Fig. 7: Classified results of Fig. 1 and 2 by means of the proposed FABCS; (a) 4 regions with Background (BKG), Gray Matter (GM), White Matter (WM) and Cerebral Spinal Fluid (CSF), respectively; (b) 5 regions with BKG, GM, WM, CSF and cerebral infarction (CI), respectively

Time (*TE*) are *TR*/*TE* = 2500 ms/75 ms for Fig. 6a and 6b. In Fig. 7a, different regions were classified by the FABCS from Fig. 1 such as Background (BKG), Gray Matter (GM), White Matter (WM) and Cerebral Spinal Fluid (CSF), respectively.

The next example is a medical image classification in head MR image of a patient diagnosed with cerebral infarction. Figure 7b shows 5 regions BKG, GM, WM, CSF and Cerebral Infarction (CI) classified by the proposed FABCS, respectively. The abnormal region with CI classified by the FABCS can be clearly classified in Fig. 7b.

CONCLUSION

An artificial bee colony system by means of fuzzy c-means with cooling schedule called Fuzzy Artificial Bee Colony System (FABCS) is proposed to medical image segmentation in this study. Every bee in the proposed FABCS owns a searching circular area with a variable radius decreased by a cooling schedule iteratively. In the searching area, the pixels classified several clusters by means of the FCM strategy to find the best local cluster centroids. Finally, the clusters' cnetroids for bees are integrated to merge near-global centroids when the iterations were terminated. In order to show the classification performance, the test phantom images can be classified into more suitable clusters by the proposed FABCS than the other strategies. In the application of MRI medical image classification, the promising results can be obtained by using of the proposed FABCS.

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