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A fuzzy image clustering method based on an improved backtracking search optimization algorithm with an inertia weight parameter

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ABSTRACT

In this paper, we introduced a novel image clustering method based on combination of the classical **F**uzzy **C**-**M**eans (FCM) algorithm and **B**acktracking **S**earch optimization **A**lgorithm (BSA). The image clustering was achieved by minimizing the objective function of FCM with BSA. In order to improve the local search ability of the new algorithm, an inertia weight parameter (w) was proposed for BSA. The improvement was accomplished by using w in the steps of the determination of the search-direction matrix of BSA and the new algorithm was named as w-BSAFCM. In order to show the effectiveness of the new algorithm, FCM was also combined with the general forms of BSA in the same manner and three benchmark images were clustered by utilizing these algorithms. The obtained results were analyzed according to the objective function and Davies-Bouldin index values to compare the performances of the algorithms. According to the results, it was shown that w-BSAFCM can be effectively be used for solving image clustering problem.

1. Introduction

Image clustering aims to separate the regions of interest of an image from any unwanted sections such as background. This process is realized as the first step in image analysis applications, in general. Image clustering has been used in many fields and several image clustering methods have been proposed by the researchers for using in several kinds of image related problems (Ahmed, 2015; Yu, 2014; Ahmed and Jalil, 2014; Biswas and Jacobs, 2014; Santhi and Murali Bhaskaran, 2014; Yang et al., 2010; Tsai et al., 2014). The FCM algorithm is one of the most known of the clustering algorithms introduced by Dunn (1973) and improved by Bezdek (1981). FCM tries to minimize an objective function which is based on the membership values of each member of a data set to the all the clusters, separately. Although, FCM algorithm can be applied to the many clustering problems, it can easily be trapped of a local minimum of the problem and high sensitive to the selection of the initial parameters such as initial cluster centers (Xu et al., 2009). In the literature several studies have been conducted to solve these problems of FCM. And, many authors proposed to use FCM with global optimization algorithms in order to increase the ability of FCM for escaping from the local minimums of the related problem. Biniaz and Abbasi (2014), combined an unsupervised Ant Colony algorithm with FCM to overcome defects of the both of the algorithms. Wang et al. (2008), proposed FCM-SLNMM clustering algorithm by using supervised learning normal mixture model and FCM together. They presented some experiments by using world data from UCI Machine Learning Repository and depicted that supervised learning normal mixture model can improve the performance of the FCM. In Taherdangkoo et al. (2010) used Artificial Bee Colony algorithm to improve performance of FCM for segmentation of MR brain images by utilizing two influential parameters introduced by Shen et al. (2005). Gao et al. (2009) used Genetic Algorithm to improve performance of FCM for pattern recognition applications. **P**article **S**warm **O**ptimization (PSO) algorithm has also been a preferred method to be combined with FCM by the researchers. Ichihashi et al. (2008), proposed a FCM based classifier and optimized the membership function and the locations of cluster centers by using PSO. Runkler and

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Katz (2006) presented two new methods for minimizing two new re-formulated forms of FCM objective function by utilizing PSO. Yong-Feng and Shu-Ling (2009), proposed a hybrid image clustering algorithm for processing of infrared images by incorporating the local search ability of FCM and the global optimization ability of PSO. Chaghari et al. (2018) proposed combination of Forest optimization algorithm and one of the local search methods called gradient method for fuzzy clustering.

BSA was introduced by Civicioglu (2013) in 2013 as a new evolutionary algorithm for solving real-valued numerical optimization problems. BSA uses two new crossover and mutation operators and has only one control parameter (Civicioglu, 2013). Therefore, it has simple structure and can be easily implemented for solving multimodal problems (Civicioglu, 2013). Although, BSA is a relatively new optimization algorithm it has been preferred by the researchers from different fields and has been combined with different algorithms for performance improvement. Kolawole and Duan (2014) presented a research for analyzing the effect of non-aligned thrust vectors on formation keeping and determining optimal thrust inclination angles for minimizing a fuel consumption dependent cost function by an improved form of BSA by chaos. Zhao et al. (2014) proposed an improved form of BSA by combining it with Differential Evolution Algorithm and breeder genetic algorithm mutation operator. They tested their algorithm on thirteen benchmark problems and reported that the improved BSA was effective and competitive for constrained optimization problems. In Duan and Luo (2014), Duan and Luo proposed an adaptive form of BSA for optimization of an induction magnometer. They used the fitness values of the solutions for determining the probabilities of crossover and mutation operators to refine the convergence performance of the algorithm. El-Fergany (2015) used BSA for assigning distributed generators along radial distribution networks and examined the performance of BSA in determining the optimal locations and sizes of these generators. Askarzadeh and Coelho (2014) combined BSA with Burger's chaotic map and used the new algorithm for estimating the unknown parameters of the electrochemical-based model of proton exchange membrane fuel cells.

As can be seen from the mentioned studies above, BSA generally was combined with different optimization algorithms. Therefore, in this study we combined BSA and FCM algorithms to improve the performance of FCM for image clustering problem. Moreover, in order to improve the local search ability of the new algorithm, we proposed an inertia weight parameter (w) to use in the steps of the determination of the search-direction matrix of BSA and called the proposed algorithm as w-BSAFCM. The image clustering was achieved by minimizing the objective function of classical FCM with w-BSAFCM. In this study, for comparative purposes, we also combined FCM with the general form of BSA in the same manner and performed the image clustering for three benchmark images, namely Lena, Mandrill and Peppers. The experiments were performed 30 times for these images and the results were analyzed according to the Davies-Bouldin index. The results were presented as tables and figures and according to the results; it was shown that w-BSAFCM outperforms the other algorithms in terms of minimization of the objective function and DBI values.

The remainder of the paper is organized as follows; the general forms of FCM and BSA were presented in Section 2. The combination procedure of FCM with an optimization algorithm, the proposed method to improve BSA and the improved form of BSAFCM, namely w-BSAFCM were described in Section 3. The experiments performed to determine the improvement in the optimization algorithm for three sample benchmark images and the results were given in Section 4 and finally, in Section 5 the paper was concluded.

2. General forms of the algorithms

BSA is a relatively new (2013) optimization algorithm and based on the most knowledge of the authors of this paper it has been not combined with FCM so far. Therefore, in order to present the general structure of the algorithms, in this section, the formulations of BSA were given in details while the well-known FCM was briefly described.

2.1. Fuzzy c-means algorithm

FCM algorithm is a clustering algorithm which is based on the minimization of an object function in an iterative process (Askarzadeh and Coelho, 2014). The clustering problem can be described as clustering the members of a data set into c clusters according to the relationships between those members. Assume the data set $H = (h_1, h_2, \ldots, h_m)$ has m members, each member h_j, has a membership value $u_{i,j}$ on the i'th cluster (Askarzadeh and Coelho, 2014). An cxm matrix that composed of all the membership values of the all the members of the data set is described as the fuzzy cluster matrix, $U = [u_{i,j}] \in [0,1]_{cxm}$ (Askarzadeh and Coelho, 2014). This matrix has some criteria given as follows (Askarzadeh and Coelho, 2014);

$$\sum_{i=1}^{c} u_{i,j} = 1, \quad 1 \leqslant j \leqslant m \tag{1}$$

$$0 \leqslant u_{i,j} \leqslant 1, \quad 1 \leqslant i \leqslant c \tag{2}$$

$$0 \leqslant \sum_{j=1}^{m} u_{i,j} < m \tag{3}$$

According to the above criteria FCM algorithm iteratively minimize the following object function (Askarzadeh and Coelho, 2014).

$$J = \sum_{i=1}^{c}\sum_{j=1}^{m} u_{i,j}^{k} D_{i,j}^{2} \tag{4}$$

where k, J and $D_{i,j}$ are fuzzifier constant, the object function and the distance between the i'th cluster center and the j'th element of the data set, respectively. $D_{i,j}$ can be written as follows (Askarzadeh and Coelho, 2014).

$$D_{i,j} = ||v_i - h_j|| \tag{5}$$

where $||\ ||$ represents eucledian distance and v_i is the center of the i'th cluster and it is described as in Eq. (6).

$$v_i = \frac{\sum_{j=1}^{m} u_{i,j}^{k} h_j}{\sum_{j=1}^{m} u_{i,j}^{k}} \tag{6}$$

Finally, the membership value $u_{i,j}$ of a member on the i'th cluster is defined as follows (Askarzadeh and Coelho, 2014);

$$u_{i,j} = \frac{1}{\sum_{r=1}^{c} \left(\frac{D_{i,j}}{D_{r,j}}\right)^{2/(k-1)}} \tag{7}$$

The flowchart of the classical FCM algorithm is given in the Fig. 1.

Stopping criterion for the classical FCM algorithm can be a maximum number for the loop or can be an coefficient ε which provides the following inequality (Askarzadeh and Coelho, 2014).

$$\max(U^{(l+1)} - U^{(l)}) < \varepsilon \tag{8}$$

where l is the iteration number and $\max(U^{(l+1)} - U^{(l)})$ is the maximum difference between all the elements of two successive U matrix in the loop.

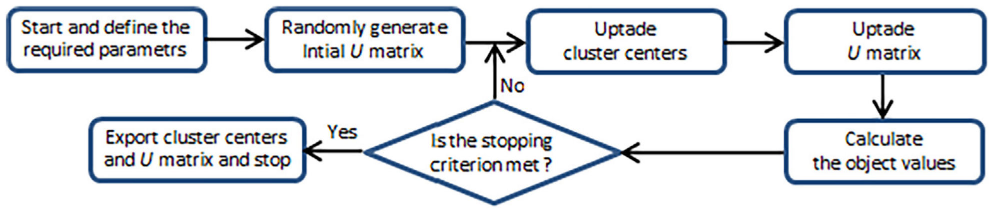

Fig. 1. Flowchart of the classical FCM algorithm.

2.2. Backtracking search optimization algorithm

BSA was introduced in Civicioglu (2013) as a new evolutionary algorithm for solving real-valued numerical optimization problems. It uses two new crossover and mutation operators while generating trial populations and also has a memory to store the randomly selected members of the previous generation for producing a search-direction matrix. BSA is simply composes of five sections explained as follows (Civicioglu, 2013);

Initialization: This section of BSA defines the initial population for optimization as given in Eq. (9) (Civicioglu, 2013).

$$S_{i,j} \sim R(\min_j, \max_j) \tag{9}$$

where $S_{i,j}$ $(i = 1,2,3,\ldots,n$ and $j = 1,2,3,\ldots,d)$ is i'th individual at the j'th dimension of the population, n and d are the maximum numbers of the individuals and the dimensions of the population, respectively while R depicts uniform distribution (Civicioglu, 2013). And, $\min_j$ & $\max_j$ are the minimum and maximum limits of the j'th dimension. In this section, BSA also determines the fitness values for the S matrix.

$$fitness = ObjectFunc(S) \tag{10}$$

where fitness is nx1 matrix of the fitness values for the S matrix and *ObjectFunc* is the object function selected for solution of the optimization problem.

Selection I: This section of BSA defines a different form of the population namely, *oldP*. *oldP* is used to determines the search direction matrix for BSA. In the initial step *oldP* is being defined as the initial population (Civicioglu, 2013);

$$olP_{i,j} \sim R(\min_j, \max_i) \tag{11}$$

Definition of the *oldP* at the other iterations except the initial step is changed according to the result of an *if then* rule as given in Eq. (12). This definition makes BSA to have a memory by randomly selection of the previous population as *oldP* and remember until is changed (Civicioglu, 2013).

$$\textit{If } r_1 < r_2 \text{ then } oldP := S | r_1, r_2 \sim R(0,1) \tag{12}$$

After determining the members of the *oldP*, BSA also changes the orders of these members by using a random shuffling function, named as *permutting* function as follows (Civicioglu, 2013).

$$oldP := permutting(oldP) \tag{13}$$

Mutation: BSA mutation process generates a trial population named as T matrix. The difference of the current population S and the *oldP* creates the search-direction matrix. The amplitude of this matrix is determined by a scale factor, F. T is obtained by adding the scaled search direction matrix to the current population.

$$T = S + F(oldP - S) \tag{14}$$

Crossover: BSA's crossover strategy uses T matrix, a mixrate parameter and n and d as inputs to obtain the final form of the trial population, namely *Mutant* matrix. Firstly, a *nxd* size map matrix of ones is defined. Then two selection strategies were used to select some individuals from T (Civicioglu, 2013).

$$\textit{If } r_1 < r_2 \text{ then } map_{i,u(1:\lceil mixrate.rand.d \rceil)} = 0|u = permutting(1,2,3\ldots,d) \textit{ else } map_{i,randi(d)} = 0 \tag{15}$$

where $randi(d)$ is a function that produces an integer number between 0 and d. The $rand \sim R(0,1)$ and *mixrate* parameters controls the number of the individuals that will be manipulated by related individuals of S matrix. As seen in the equation *if* $r_1 > r_2$ then only one indivual will be selected for manipulation in each trial (Civicioglu, 2013). With the help of the *map* matrix, except the selected individuals (which equals to 0), all the other individuals of the T matrix are changed by the related individuals of the S matrix. And, the final form of the T matrix, the *Mutant* matrix is obtained (Civicioglu, 2013).

$$\textit{If } map_{i,j} = 1 \textit{ then } T_{i,j} = S_{i,j} \; (i = 1,2,3,\ldots,n; \; j = 1,2,3,\ldots,d) \tag{16}$$

$$Mutant = T \tag{17}$$

The *Mutant* matrix may include some individuals that overflow the search space limits. Such individuals are re-determined randomly as doing in the Eq. (9).

Selection II: In this section BSA determines the fitness values of the individuals of the *Mutant* matrix by using *ObjectFunc* and then updates the members of the *fitness* vector and the S matrix as follows (Civicioglu, 2013);

$$fitnessM = ObjectFunc(Mutant) \tag{18}$$

$$\textit{If } fitnessM_{i,j} < fitness_{i,j} \textit{ then } fitness_{i,j} = fitnessM_{i,j} \textit{ and } S_{i,j} = Mutant_{i,j} \tag{19}$$

The last four section simply defined above (except initialization) repeats until BSA reach the maximum cycle number. At the end of the algorithm, minimum value of the *fitness* vector is accepted as the *global minimum* and the related individual of the S matrix according to the *global minimum* is defined as the *global minimizer*. A simple flowchart of the BSA algorithm is given in Fig. 2.

3. Combination FCM with an optimization algorithm

FCM algorithm can be used to solve many clustering problems, especially image clustering problems. However, it is very sensitive to the selection of the initial cluster centers (Yong-Feng and Shu-Ling, 2009) and also it can easily be trapped of the local minimums of the problem. Therefore, many authors proposed to combine FCM with another optimization algorithm to overcome these problems. Generally, the combination procedure can be made in two different manners. The first one is determining the initial cluster centers for classical FCM by using the selected optimization algorithm, while the second is minimizing the objective function of FCM by using the optimization algorithm (Runkler and Katz, 2006). In this study we chose the latter method to combine FCM with BSA. Therefore, we determined a general structure for the populations of the optimization algorithm.

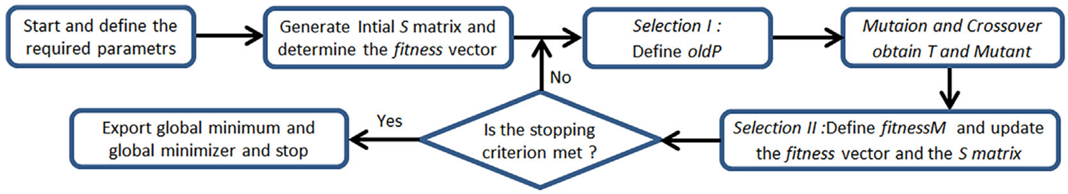

Fig. 2. Flowchart of the BSA algorithm.

$$S = \begin{bmatrix} S_{1,1} & \cdots & S_{1,c} \\ \vdots & \cdots & \vdots \\ S_{n,1} & \cdots & S_{n,c} \end{bmatrix} \tag{20}$$

In the equation each row of the S matrix is a candidate solution to the problem and includes a set of cluster centers. Where, c is the number of the cluster centers while n is the number for the population size. With the help of the Eqs. (4), (5), (7) and (20) the combination procedure can be realized. In order to present the procedure in details, in the following section, the steps of the combination procedure for FCM with BSA were explained.

3.1. Fuzzy clustering based on BSA

Classical FCM algorithm and BSA can be combined to minimize the objective function of FCM by utilizing BSA as explained in the following steps.

Step 1: Obtain the gray scale form of the image that will be clustered. And, define the initial parameters for the both algorithms. These parameters are population size (n), stopping criterion, *mixrate* and scale factor (F) for BSA and the cluster number and fuzzier constant (m) for FCM.

Step 2: Define the initial population for BSA as given in the Eq. (20).

Step 3: Generate *fitness* vector by using the Eqs. (4), (5) and (7) for each cluster center set given by S.

Step 4: Start BSA loop and in each loop obtain the *fitnessM* vector as given in the Step 3 and update the *fitness* and S.

Step 5: If the stopping criterion is met stop the BSA loop and export the *global minimum*, *global minimizer* and the final form of the U matrix.

Step 6: Generate c clustered images by using the obtained U matrix.

The flowchart of the proposed algorithm is given in Fig. 3.

In the figure the blue boxes represent the parts from BSA while the two red boxes represent the parts about classical FCM.

3.2. w-BSAFCM

BSA has very powerful exploration and exploitation capabilities (Civicioglu, 2013) and FCM can show a good performance as a local search algorithm if the effective initial cluster centers are given. By combining these two algorithms the sensitiveness problem of FCM to the selection of initial cluster centers can be resolved. On the other hand, in order to make the BSA-FCM combination is competitive to the combinations of FCM with the other optimization algorithms, we defined an inertia weight parameter (w).

$$w_{t+1} = w_{min} + \exp\left(-\exp\left(-(t_{max} - t) * \frac{(w_{max} - w_{min})}{t_{max}} * w_t\right)\right) \tag{21}$$

Table 1
The parameters used for image clustering for all the algorithms.

The algorithms	Algorithm-specific control parameters	Common control parameters
w-BSAFCM	$k = 2, mixrate = 1, w_{min} = 0.2, w_{max} = 0.9$	$k = 2$, $c = 3$, $t_{max} = 40$, $n = 40$
BSAFCM	$k = 2, mixrate = 1, F = 3r_3 \| r_3 \sim R(0,1)$	

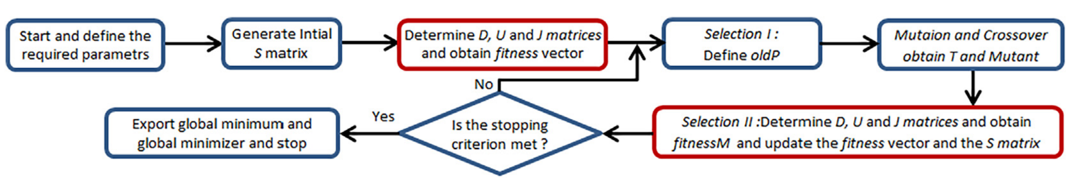

Fig. 3. Flowchart of the combination of BSA with FCM.

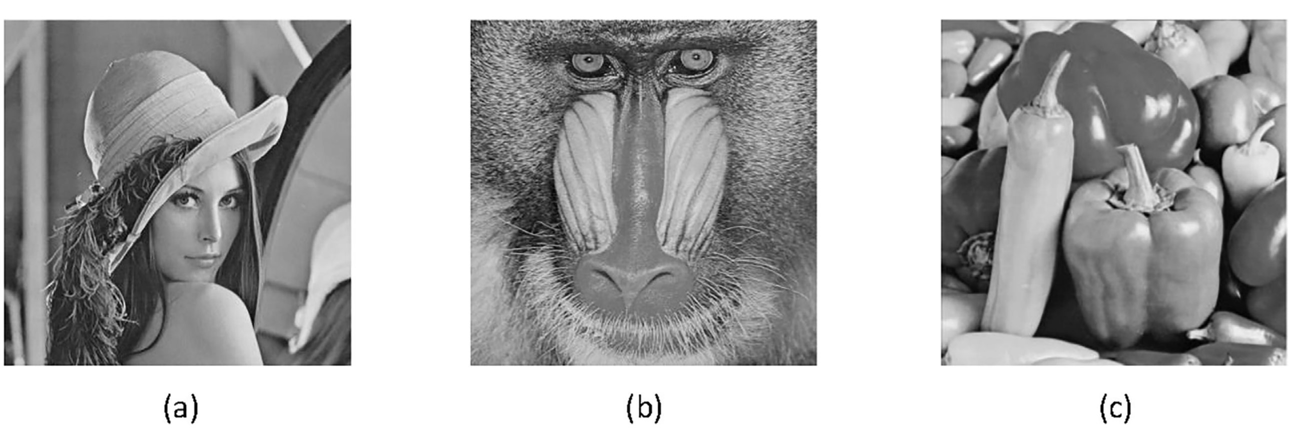

Fig. 4. The original forms of the three benchmark images (a) Lena, (b) Mandrill (c) Peppers.

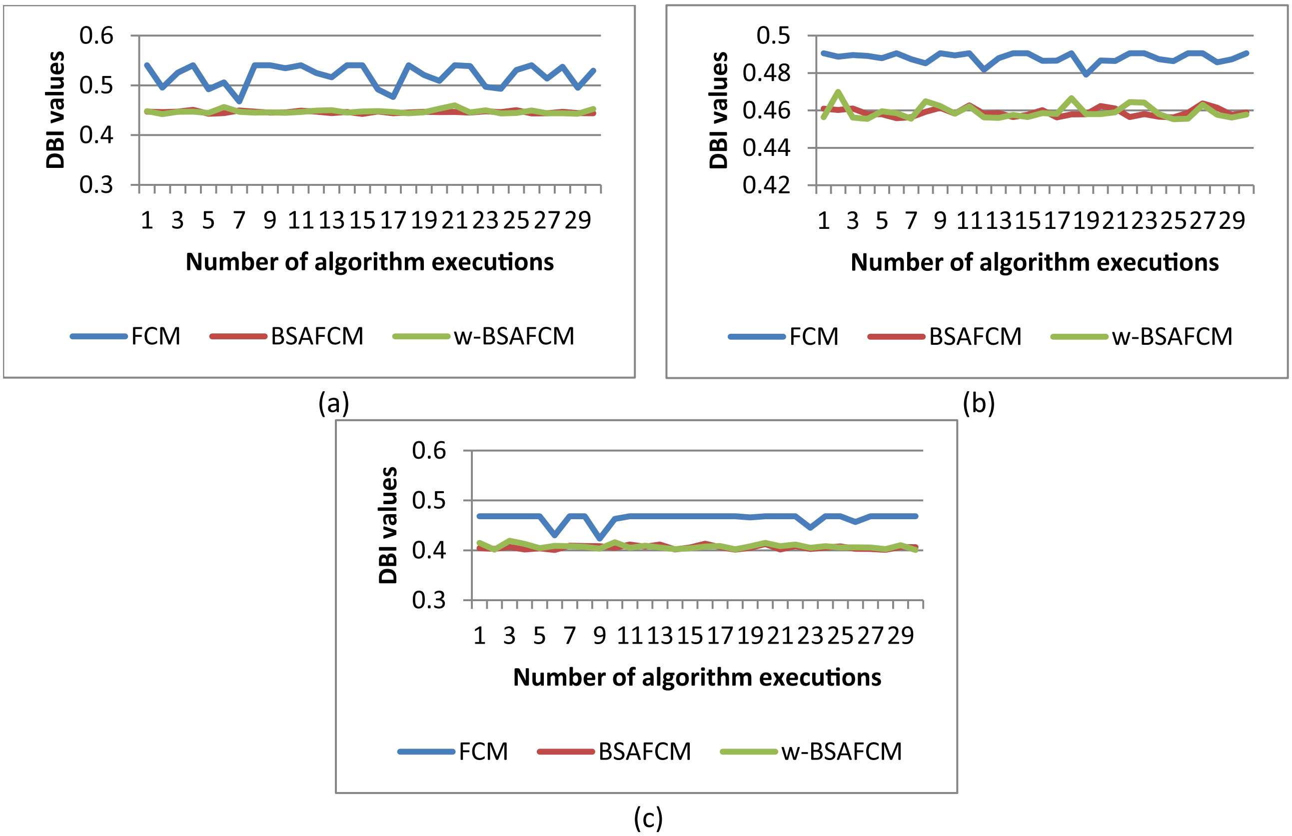

Fig. 5. The best DBI values obtained in all the executions of the algorithms for the three images (a) Lena, (b) Mandrill (c) Peppers.

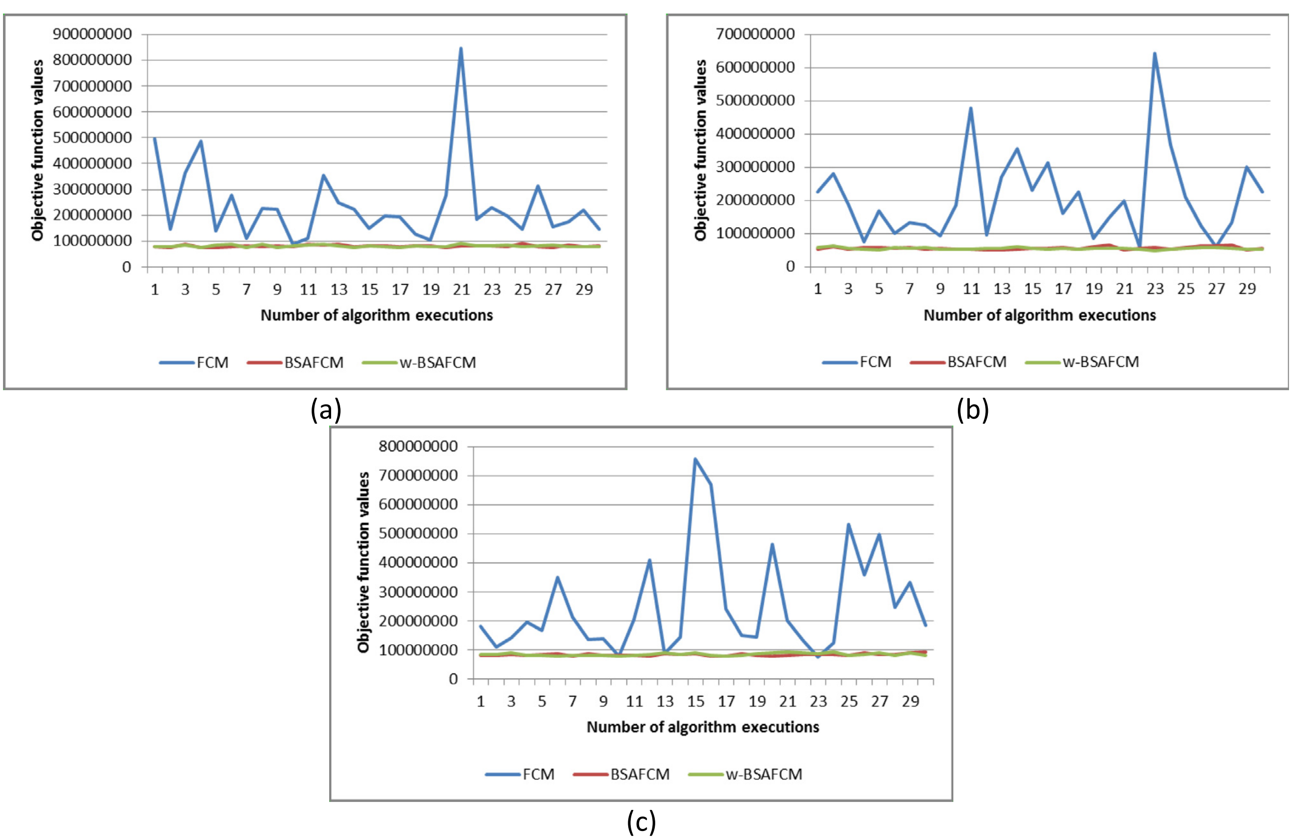

Fig. 6. The objective function values calculated for the clustering solutions that give the best DBI values for the three images (a) Lena, (b) Mandrill (c) Peppers.

where t and t_{max} are the current and the maximum numbers of the iterations and w_{min} and w_{max} are the limits of the minimum and maximum values of 'w', respectively. Finally w_t is the 'w' at the t'th iteration while exp depicts exponential function. As can be seen from the equation, w can vary according to the selection of w_{min}, w_{max} and the number of the iterations. Definition of w_{t+1} requires 'w' from the previous iterations. So, the first 'w' is defined by uniform distribution between 0 and 1.

In order to increase the local search ability of the new algorithm we used w in generating of the search-direction matrix of BSA. Generating of search direction matrix is highly related to the selection of *oldP* as given in the Eq. (12). According to this equation it can be seen that the selection procedure of *oldP* is a pure random procedure. Such a selection makes BSA to have equal possibility of conducting the search direction of the algorithm to a global minimum by selecting a new randomly generated *oldP* or to a local minimum by selecting an *oldP* from the previous form of the population. So as to increase the local search ability of the new algorithm we used 'w' parameter to determine the *oldP* with a high possibility of selection from the previous form of the population. Therefore, Eq. (12) can be re-written as follows;

$$\textit{If } r_1 < w \text{ then } oldP := S | r_1 \sim R(0,1) \tag{22}$$

Local search abilities of BSA are not only related to the selection of *oldP* but also related to determining of the amplitude of the search-direction matrix. In the Eq. (14), F determines the amplitude of this matrix. Therefore, we defined F as follows to obtain a scale factor that can be not only randomly determined but also determined by 'w'.

$$\textit{If } r_1 < r_2 \text{ then } F := \text{w else F} = 3\text{r}_3 | r_1, r_2, r_3 \sim R(0,1) \tag{23}$$

With help of the 'w' parameter the combination of BSA-FCM can be called as w-BSAFCM that has higher local search abilities than its first form (BSAFCM).

4. Experiments

In order to test the w-BSAFCM algorithm, three sample benchmark gray scale images, Lena, Mandrill and Peppers were selected. All the three images have 512 × 512 sizes and were given in the Fig. 4. Image clustering were performed for all the images for three cluster numbers, $c = 3$, by classical FCM, BSAFCM and w-BSAFCM.

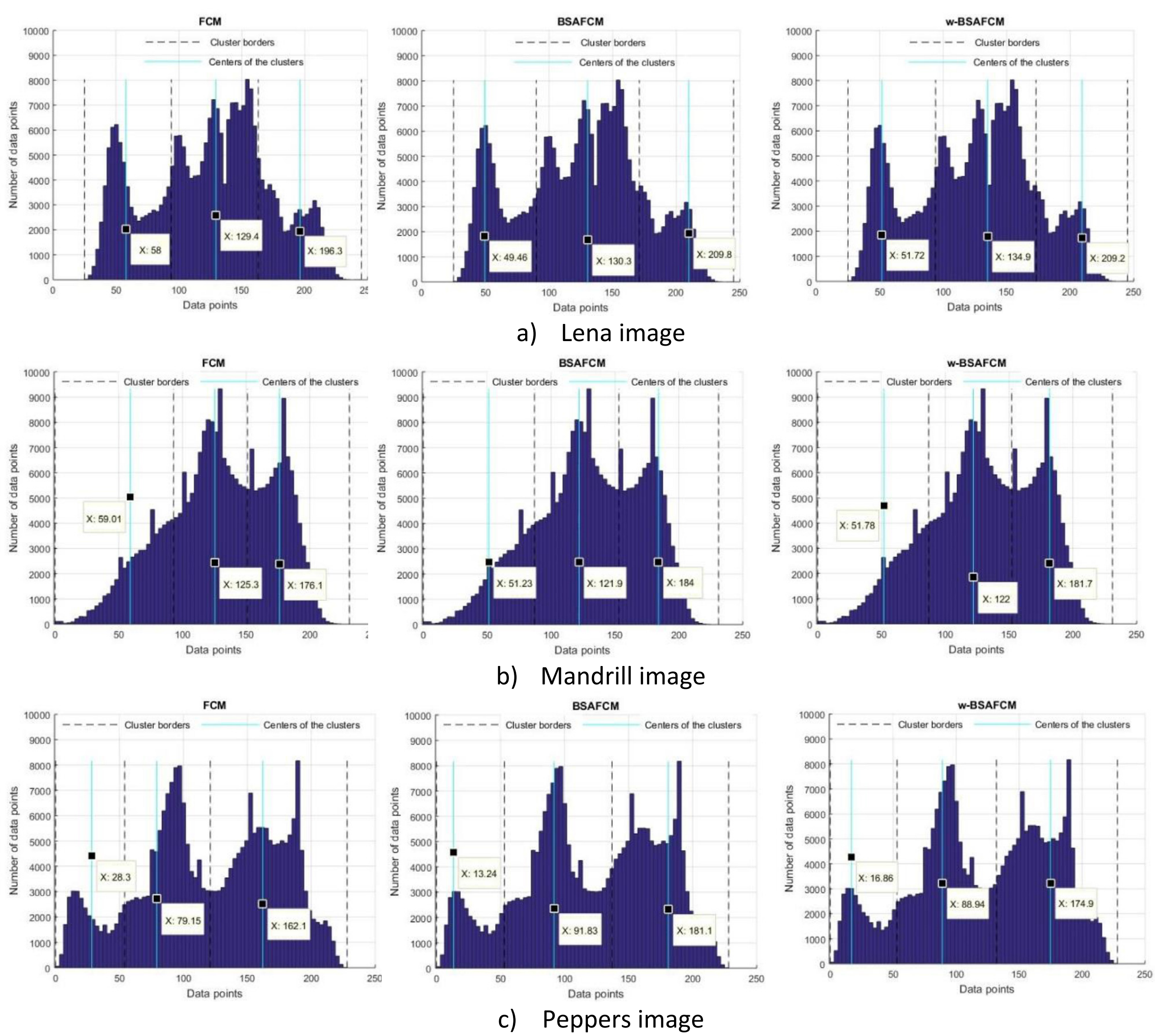

Fig. 7. Histogram graphics of the best clustering solutions of the three algorithms for the test images.

Table 2
Best performance numbers of the algorithms in 30 executions.

Algorithms	Best performance numbers					
	DBI values			Objective function values		
	Lena	Mandrill	Peppers	Lena	Mandrill	Peppers
w-BSAFCM	15	17	10	17	19	13
BSAFCM	15	13	20	13	11	14
FCM	0	0	0	0	0	3

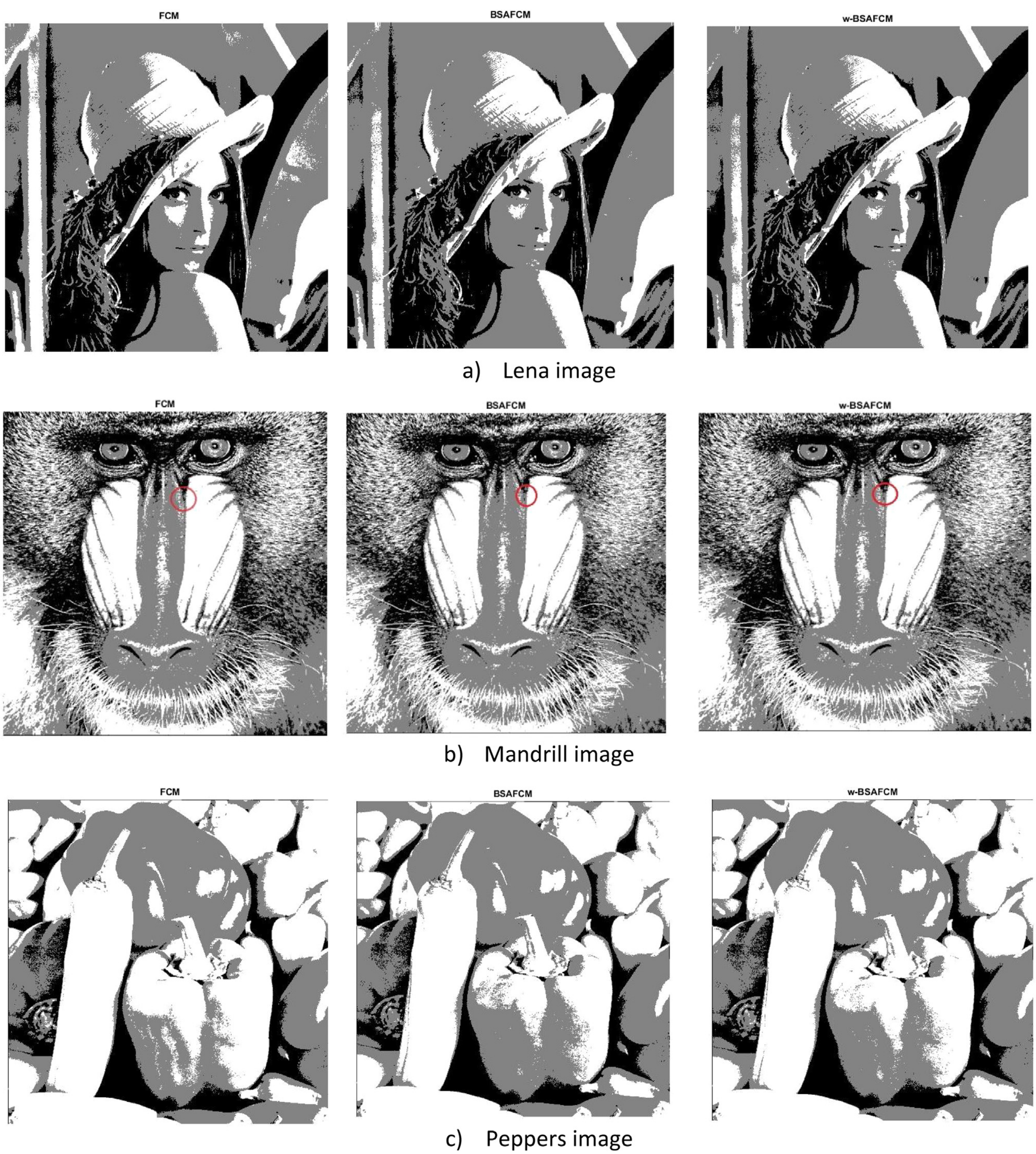

Fig. 8. Clustered images with the best clustering solutions of the three algorithms for the test images.

Algorithm-specific control parameters and common control parameters for all the optimization algorithms were given in Table 1. It should be noted that, since all the parameters of the classical FCM are also in the common parameters of combination of FCM with the other algorithms, classical FCM was not included in the table.

The experiments were performed 30 times for each of the three images for the used optimization algorithms, the initial populations of each run were randomly generated and the stopping criterion was defined as the maximum number of the iterations. All the experiments and analyses were performed on a PC equipped with Intel I3 3.10 GHz CPU and 4 GB RAM by using Matlab.

In order to evaluate the clustering performance of the algorithms Davies-Bouldin Index (DBI) was used. DBI is proposed by Davies and Bouldin (1979) and based on the ratio of the sum of within cluster-scatter to between-cluster separation (Ozturk et al., 2015).

$$P_i = \frac{1}{n_i}\sum_{h_j \in c_i} D(h_j, \upsilon_i)^2 \quad (24)$$

$$R_{i,j} = \frac{P_i + P_j}{D(\mathrm{v}_j, \upsilon_i)^2} \; i \neq j, \quad i = 1, 2, \ldots, c \quad (25)$$

$$DBI = \frac{1}{c}\sum_{k=1}^{c} R_k \quad (26)$$

where $\mathrm{R_k} = \max(\mathrm{R_{i,j}})$.Where c_i and υ_i defines the i'th cluster and its center, and n_i, and h_j are the number of the elements of the i'th cluster and the j'th element of that cluster, respectively. In the experiments the clustering solutions (cluster centers and the objective function values) of the algorithms that obtain the minimum DBI values were recorded and used to present the comparisons between the performances of the algorithms. The results of the DBI values were given in Fig. 5 and the results of the objective function values were given in Fig. 6 for all the executions of three algorithms.

According to the Figs. 5 and 6, it can be seen that the BSAFCM and w-BSAFCM algorithms shown better performance than the classical FCM algorithm for both in minimizing the DBI and objective function values. On the other hand from the figures, the difference between w-BSAFCM and BSAFCM algorithms cannot be seen clearly. Therefore, in order to show the difference between the performances of these two algorithms, the best performance numbers of the algorithms in 30 executions were given in Table 2.

According to the Table 2, in terms of minimizing DBI value, w-BSAFCM gets the best results for the Mandrill image while BSAFCM gets the best results for the Peppers image and the two algorithms gets the same result for the Lena image. On the other hand, in minimizing objective function value w-BSAFCM outperforms the other two algorithms for the Lena and Mandrill image. The only image that the BSAFCM shows the better performance is the Peppers image.

Since the test images have 262,144 data points the histogram graphics were preferred to visualize the clustering solutions. Therefore, histogram graphics of the three images were given with the best clustering solution of the three algorithms in Fig. 7. On the each figure the cluster borders and the centers of the clusters were depicted. And also, the clustered images that were drawn according to the best solutions of the algorithms were given in Fig. 8.

The relations between the cluster centers, their borders and the histogram of the images can be evaluated to compare the clustering performance of the algorithms. As an example, for the Lena image, the most repetitive numbers from the left are between the data points 48 and 52. From a practical point of view, it can be said that the first cluster center should be near this interval. From Fig. 7, it can be seen that the first cluster center found by the classical FCM algorithm is 58 while it is 49.46 for BSAFCM and 51.72 for w-BSAFCM. Therefore it can be said that the BSAFCM and w-BSAFCM shows better performance than the classical FCM. The same results can be derived from the clustered images in Fig. 8. An example region was circled on the clustered Mandrill images. According to these circled regions it can be seen that some details from the original image are exist in the circles on the resultant images of the BSAFCM and w-BSAFCM algorithms while they are not been seen in the clustered image by the classical FCM algorithm.

5. Conclusions

One of the most used image clustering algorithms, FCM was combined with a new population based optimization algorithms BSA. And, a novel image clustering algorithm w-BSAFCM was introduced to incorporate the local search ability of FCM algorithm and the global search ability of BSA. An inertia weight parameter (w) was proposed to improve the local search ability of the new algorithm. The w parameter was used in the steps of the determination of the search-direction matrix of BSA. In order to present a general comparison classical FCM algorithm was also combined with the general form of BSA in the same manner and the algorithms were used to cluster three benchmark images. According to the results, it was shown that w-BSAFCM can be effectively used in solving image clustering problem.

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