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Enhanced Butterfly Optimization Based Clustering for Digital Images

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Abstract: Butterfly Optimization Algorithm (BOA) is a metaheuristic optimization algorithm mathematically modelling the foraging behaviors of butterflies for solving optimization problems. This article first modifies the BOA by incorporating sudden and fast movements of butterflies for escaping from predators. Segmentation of digital images is a vital process in classification, object recognition and other computer vision applications. Clustering is a class of segmentation that can relate one pixel to many classes of the given digital image. This article formulates such clustering method as an optimization problem suitable for metaheuristic environment by defining the butterfly to represent cluster centroids and developing a fitness function from the cost function of the classical fuzzy method (CFM). It then applies the enhanced BOA (EBOA) for obtaining optimal centroids. This article presents the results of the proposed method on six digital images and compares its performance with the CFM.

Keywords: *Meta-heuristic algorithms, image segmentation, fuzzy based clustering, butterfly optimization.*

1. Introduction

Image segmentation is a complex computational procedure of extracting a region of interest or dividing an image into many regions based on texture, intensity, position, etc. This process in fact assigns a same label to pixels with similar features. It helps to interpret the image in a more meaningful way than that of handling the original image. It represents the most significant task in computer vision applications, especially in object recognition, classification, fault diagnosis, medical diagnosis, pattern recognition, surveillance, etc. [1]. It plays a significant role in medical images for finding lesion dimensions, abnormal structure, odd texture, computer aided surgery, and so on. Each application requires a specific segmentation method. For example, the segmentation of an object in a photograph will be totally different from that of segmenting a cancer region in brain images. A generalized segmentation method is not yet developed for obtaining satisfied results for all kinds of digital images and applications, but the radiologists require a flexible segmentation technique for segmentation of lesions in medical images [2].

Several segmentation methods, outlined in recent years, can be divided into threshold-, deformation- and clustering-based schemes. The former one obtains the best thresholds and then divides the image based on the thresholds [3-5]; the second one uses region growing [6] and level set [7] techniques for segmentation of lesions and is semi-automatic as it requires manual initial points; the last one forms many clusters using techniques like K-means [8] and Fuzzy C-means (FCM) [9] algorithms. The particle swarm optimization (PSO) was employed for finding the clusters of medical images [10]. The artificial bee colony (ABC) was used to determine the best thresholds in monochrome images [11,12]. The ant colony optimization (ACO) was employed for extracting blood vessels in fundas images [13] and for detecting edges of flowers [14]. The teaching-learning algorithm was applied for detecting the edges of skin lesions [15]. The chemical reaction algorithm and level sets were applied for clustering and segmenting the cancerous region for medical images [16]. A K-means clustering with graphical-segment scheme was outlined for delineating the tumour parts in skull images [17]. The level-set technique was applied for delineating hippocampus in MRIs for diagnosing Alzheimer [18]. A computer-based 3D tree approach was suggested for segmenting ducts in tomography images of salivary glands [19]. The cancer parts in breast images were segmented through a technique involving roulette wheel based mean shift technique [20]. The football game algorithm and level-set technique were employed for clustering and segmenting cancerous regions in medical images [21]. Among them, threshold and clustering based methods are very generalized methods applicable for all kinds of images, while the deformation approach is to be developed for a specific application. The fuzzy methods can relate one pixel to many classes, thereby suiting them for medical image analysis.

Recently, a Butterfly Optimization Algorithm (BOA), inspired from the foraging behaviours of butterflies, was proposed for solving optimization problems, and illustrated to be superior than the existing metaheuristic/classical optimization algorithms [22]. This article aims to enhance the BOA by incorporating sudden and fast movements of butterflies for escaping from predators and employing this enhanced BOA (EBOA) for obtaining optimal cluster

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centroids for robust clustering for digital images, and studying its performance for different types of images.

The article is formed into four sections. Section 1 introduces the segmentation, section 2 proposes EBOA based clustering method (ECM), section 3 discusses the performances of the developed scheme and section 4 concludes.

2. Proposed Clustering Method

The ECM requires image preprocessing, variable identification, and representation, tailoring of a fitness function, and employment of EBOA. Digital images contain noises and require denoising. Among the various denoising filters [23], median filter is employed for image denoising in the proposed method. Besides, the color images are converted into two dimensional monochrome images.

2.1. Equations

In proposed clustering method, the centroids of each cluster are considered as unknown problem variables. Each butterfly in the EBOA is defined to denote the n-number of centroids as

$$Bf_i = [C_1,\ C_2,\ \cdots\ ,\ C_n] \tag{1}$$

Each butterfly is constrained to satisfy the lower and upper limits as

$$Bf^{min} = [0, \quad 0, \quad \cdots, \quad 0 \quad] \tag{2}$$

$$Bf^{max} = [255,\ 255,\ \cdots,\ 255] \tag{3}$$

2.2. Tailoring of a Fitness Function

The values of butterfly should be optimized to maximize a predefined fitness function (Ψ), that is derived from the cost function (Φ) of the fuzzy C-means clustering technique employing a fuzzy membership function.

$$Maximize\ \Psi = \frac{1}{1+\Phi} \tag{4}$$

Where

Φ is the objective function to be minimized, and can be represented by

$$\Phi = \sum_{i=1}^{n} \sum_{j=1}^{m} \theta_{ij}^{\gamma} \left\| I_j - C_i \right\|^2 \tag{5}$$

I_j is the intensity of j-th pixel

γ is a parameter influencing the fuzziness (>1)

C_i is the i-th centroid

θ_{ij} is the membership function i-th centroid with j-th pixel of the image, and can be computed by

$$\theta_{ij} = \frac{\left\| I_j - C_i \right\|^{-2/(\gamma-1)}}{\sum_{k=1}^{n} \left\| I_j - C_k \right\|^{-2/(\gamma-1)}} \tag{6}$$

The membership is constrained by

$$0 \le \theta_{ij} \le 1 \tag{7}$$

2.3. BOA

The fragrance (F) of a butterfly is evaluated from the Ψ as

$$F = \rho \Psi^{\eta} \tag{8}$$

Where ρ and η are the sensory and the absorption parameters respectively.

The i-th butterfly makes a global move towards the best butterfly (Bf^*) possessing the greatest fitness.

$$Bf_i^{t+1} = Bf_i^t + \delta^2 \times (Bf^* - Bf_i^t) \times F_i^t \tag{9}$$

It also makes local move by

$$Bf_i^{t+1} = Bf_i^t + \delta^2 \times \left(Bf_j^t - Bf_k^t\right) \times F_i^t \tag{10}$$

Where

$$t < T^{max} \tag{11}$$

Bf_i^t is the i-th butterfly at t-th instant.

δ is a randomly generated number.

F_i^t is the smell of i-th butterfly at t-th instant.

T^{max} is the specified permissible number of generations.

2.4. Enhancement in BOA

Practically, the global and local moves are insufficient in the presence of predators. If butterflies find predators like sparrows, mynas, etc., they make sudden and fast movements for escaping from the predators. It is considered that each butterfly memorizes the best and safest position (Bf_i^*) seen by it so far. The sudden and fast movement is represented through Eq. (12) involving Levy Flight technique, and controlled by a switching parameter, Ω∈[0,1], during the iterative process.

$$Bf_i^{t+1} = Bf_i^t + \mu \aleph \ (Bf_i^t - Bf_i^*) \times F_i^t \tag{12}$$

Where

$$\aleph \approx \frac{\delta\ G(\partial)\, sin(\pi\partial/2)}{\pi}\frac{1}{ss^{1+\delta}}, \qquad (ss >> ss_o > 0) \quad (13)$$

$G(\partial)$ is a gamma function

μ represents a scaling factor that controls the step size .

∂ denotes a constant.

Bf_i^* represents the safest memorized position of i-th butterfly.

2.5. Algorithmic Steps

A swarm of butterflies are randomly generated as defined in Eq. (1) subject to the constraints of Eqs. (2) and (3). The fitness (Ψ) and the fragrance (F) of all the members in the swarm are computed. Each member in the swarm then performs a local and global move probabilistically in the problem space, and its fitness and fragrance are computed. This iterative process is continued for a specified permissible no of generations. After convergence, the member in the swarm with greatest fitness (Ψ) denotes the final best centroids. The pseudo code of the solution process is outlined below:

- *Read the digital image for clustering.*
- *If the image is color image, convert it into two-dimensional monochrome image.*
- *Apply median filter for image denoising.*
- *Define butterfly parameters like swarm size, ρ, η, and T^{max}.*
- *Define butterfly as in Eq. (1).*
- *Randomly form a swam of butterflies as in Eq. (1) subject to constraints of Eqs. (2) and (3).*
- *Set the iteration counter $t = 1$.*
- *Repeat the following until $t > T^{max}$:*
  - ✓ *Evaluate the fitness (Ψ) and the fragrance (F) of all the members in the swarm.*
  - ✓ *Obtain the best member in the swarm with greatest fitness.*
  - ✓ *Probabilistically perform a local or global move in the problem space for all the members in the swarm.*
  - ✓ $t = t + 1$

End

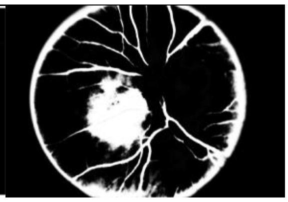
- *The best member in the swarm with greatest fitness (Ψ) denotes the final best centroids.*

3. Results and Discussions

Table 1. Test Images

	
Image-1 (Lotus)	Image-2 (Eye)
	
Image-3 (Safari Ride)	Image-4 (Plants)
	
Image-5 (Leaves)	Image-6 (Temple)

Table 2(a). Clustered Image Sets

Cluster	Image-1	Image-2
1		
2		
3		

The ECM was applied on six digital images comprising of lotus, fundus, safari ride, plants, leaves, and temple as given in Table1. All these images are downloaded from the websites and their sizes are not altered, but preprocessed for converting into gray scale and noise removal by median filter. The number of clusters was set to be 3 for all images other than fundus image, where it was raised by one to discard the black border region. The performances of the proposed method were compared with those of the classical fuzzy method (CFM) for exhibiting its superior performance.

Table 2(b). Clustered Image Sets

Cluster	Image-3	Image-4
1		
2		
3		

The results of the ECM were obtained and presented in Tables 2(a), 2(b) and 2(c), each for two test images. Each column of Table 2 contains three clustered images. In these images, a pixel closer to the corresponding centroid is denoted by a whitish pixel, and becomes greyish if the pixel intensity is away from the centroid, and vice-versa. For example, the first clustered image of the lotus focuses the region other than the lotus, and the centroid lies in that region; the second clustered image focuses on the lotus region, and the third region focuses the border regions of the lotus petals with dark pink color. These regions are automatically identified by the proposed method through maximizing the fitness of Eq. (4) by the EBOA.

Table 2(c). Clustered Image Sets

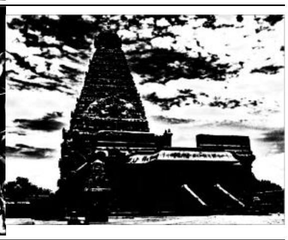
Cluster	Image-5	Image-6
1		
2		
3		

Table 3. Comparison of Centroids.

Image No	**ECM**	**CFM**
1	26.3109	183.2648
	182.8547	121.2145
	120.7607	25.6304
2	118.7845	86.3753
	84.4646	5.6296
	5.8567	118.7351
3	46.0999	51.1858
	211.2689	210.4614
	122.8956	126.4335
4	83.6993	184.2334
	238.6434	81.0729
	182.9596	239.2484
5	48.2034	47.5036
	167.3358	113.9529
	112.9209	168.2335
6	122.8390	50.9467
	174.1952	175.9676
	56.0565	125.9623

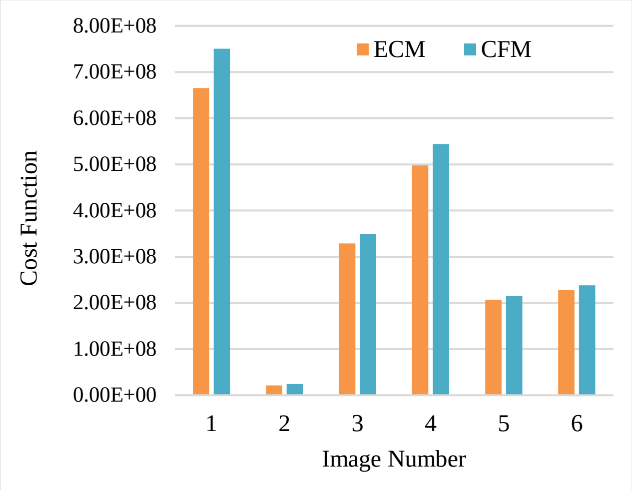


Fig. 1. Cost Function Values

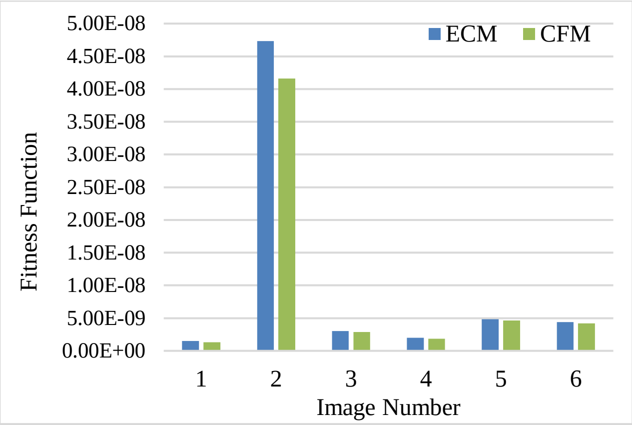


Fig. 2. Fitness Function Values

The optimal centroids of the proposed ECM and CFM are presented in Table 3. The corresponding cost and fitness function values of both methods are graphically presented in Figs. 1 and 2 respectively. It is very clear Fig. 1 that the cost function values of the proposed ECM are comparatively lower than that of CFM for all the test images. Similarly, the fitness function values of the proposed ECM are comparatively larger than that of CFM for all the test images. These lower cost function and larger fitness function value of the ECM indicate that the developed clustering scheme is better than that of the CFM. It is obvious from the above discussions that the proposed ECM is superior and suitable for clustering digital images.

4. Conclusion

BOA is a metaheuristic optimization algorithm mathematically modelling the foraging behaviors of butterflies for solving optimization problems. The performance of the BOA has been improved by incorporating sudden and fast movements of butterflies for escaping from predators. The developed EBOA has been applied for obtaining optimal cluster centroids for robust clustering for digital images. The classical fuzzy clustering method has been modified to suit the EBOA environment by defining the butterfly to represent cluster centroids and developing a fitness function from the cost function of the CFM. The developed ECM has been applied on six digital images for portraying the superior performances and showcased that the ECM successfully maximizes the fitness function through searching the problem space in arriving at the robust centroids.

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Author contributions

Janani Priya Mohan: Conceptualization, Methodology, Software, Writing-Original draft preparation, Validation. **Yamuna Govindarajan:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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