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A Multilevel Thresholding Approach Based on L´evy-Flight Firefly Algorithm for Image Segmentation

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Abstract— **Multilevel thresholding is an important technique for image processing. The maximum entropy thresholding (MET) has been widely applied in the literature. This paper presented a novel optimal multilevel thresholding approach based on the maximum entropy measure and L´evy-Flight Firefly Algorithm (LFA) for image segmentation. This new method was called, the maximum entropy based on l´evy-flight firefly algorithm for multilevel thresholding (MELFAT) method. In this paper, five famous benchmark images were used to evaluate the proposed method and the results were evaluated by the uniformity measure. The obtained results were compared with five well-known methods, like Gaussians mooting method (Lim, Y. K., & Lee, S. U. (1990), Symmetry-duality method (Yin, P. Y., & Chen, L. H. (1993), improved GA-based algorithm (Yin, P. -Y. (1999), the hybrid cooperative-comprehensive learning based PSO algorithm (HCOCLPSO) (Maitra, M., & Chatterjee, A. (2008)) and a new social and momentum component adaptive PSO algorithm (SMCAPSO) (Chander, A.,& Chatterjee, A.,& Siarry, P.(2011)) . The experimental results confirmed the performance and capability of the proposed method to find optimal threshold values.**

Keywords-component; multilevel thresholding; entropy; image segmentation; uniformity; levy-flight firefly algorithm.

I. INTRODUCTION

Segmentation is a technique which decomposes an image into meaningful parts or objects. Most computer vision and image analysis problems require a segmentation technique as a pre-processing step for detecting objects or dividing the image into regions, or homogeneous parts according to some given criteria such as color, motion, texture, etc [1]. The image thresholding is widely used in halftone reproduction [2], infrared image segmentation [3], automatic target recognition [4], color image segmentation [5] and mixed-type document analysis [6]. Single or multilevel thresholding is an effective approach for image segmentation. Bi-level thresholding selects only one threshold to place a pixel into two classes, whereas multilevel thresholding determines multiple thresholds which place pixels into several groups. Thresholding techniques can be classified into two types: of optimal thresholding methods and property based thresholding methods [7]. Optimal thresholding methods search for the optimal thresholds which make thresholded classes on the histogram. Property-based thresholding methods are fast and suitable for the case of multilevel thresholding, when the number of thresholds is hard to determine and should be specified in advanced. Kapur and Sahoo, proposed a method for gray-level image thresholding using histogram entropy [8].

Nature inspired meta-heuristic algorithms are becoming more powerful for solve optimization problems [9]. Particle Swarm Optimization (PSO) [10], Ant Colony Optimization (ACO) [11], Artificial Fish Swarm Algorithm (AFSA) [12] and Bee Colony [13] are the most well-known algorithms thus far. The Firefly algorithm, recently introduced by X. S. Yang, has been also considered as a typical swarm-based approach for optimization [14]. Yang has also introduced a new version of FA, L´evy-Flight Firefly Algorithm (LFA) [15], which combines l´evy-flight with search strategy via the Firefly for improving the randomization of FA. Some characteristics of the firefly algorithm that make it suitable for solving optimization problems are higher converging rate and flexibility.

This paper applied the l´evy-flight Firefly algorithm to search for the optimal multilevel thresholds using the maximum entropy (MET) criterion. This proposed method was called the maximum entropy based L´evy-Flight Firefly Thresholding (MELFAT) algorithm. The proposed segmentation method was employed for five benchmark images including: 'Lena', 'Peppers', 'Bird', 'Cameraman' and 'Gold hill '. The performance of the proposed algorithm was evaluated by the uniformity measure and the results were compared with those of Gaussian smoothing method [16], Symmetry-duality method [17], improved GA-based algorithm [18], the hybrid cooperative-comprehensive learning based PSO algorithm (HCOCLPSO) [19] and a new social and momentum component adaptive PSO algorithm (SMCAPSO) [20] for image segmentation.

The rest of the paper is organized as follows. In Section 2, we review several previously proposed methods, Section 3 reviews l´evy-flight firefly algorithm. In Section 4 briefly describes the entropy measure and presents the MELFAT method. The experimental results are reported in Section 5. Section 6 concludes this paper.

II. RELATED WORKS

There are many image thresholding studies in literature over the years. Comprehensive surveys of global thresholding methods can be found in [21-23]. A great number of thresholding methods with parametric or non-parametric types have been proposed in order to perform bi-level thresholding [23-25]. Thus far, several algorithms have been proposed, which have addressed the issue of optimal thresholding [26-29]. While many of such algorithms address the bi-level thresholding issue, others have considered the multilevel problem. Many such schemes attempt to achieve optimal thresholding such that the thresholded classes achieve some desired characteristics.

Currently, several such methods of designing the desired characteristic for evaluating segmentation algorithms have been proposed. Methods based on optimizing an objective function include maximization of posterior entropy to measure homogeneity of segmented classes, maximization of the measure of separability on the basis of between-class variance [30], thresholding based on the index of fuzziness and fuzzy similarity measure [31-32], etc. Kittler and Illingworth proposed a thresholding method that approximated the histogram by a mixture of normal distributions and minimized the classification error probability [33]. Several such methods have been originally developed for bi-level thresholding and later they were extended to multilevel thresholding, e.g. methods described in [8] and [30]. All of these methods have a common problem the computational complexity rises exponentially when extended to multilevel thresholding due to employed exhaustive search [20].

Kapur, Sahoo, and Wong proposed a method for gray-level picture thresholding using the histogram entropy [8]. Abutaleb proposed a 2-D maximum entropy thresholding method for separating the regions of image [34]. Zhang and Liu adopted the particle swarm optimization algorithm in order to maximize the entropy for underwater image segmentation [35].

Madhubanti and Amitava proposed a hybrid cooperative-comprehensive learning based PSO algorithm (HCOLPSO) based on the maximum entropy criterion [19]. Yin developed a recursive programming techniques for reducing the order of magnitude of computing the multilevel thresholds which used the PSO algorithm later on so as to minimize the cross entropy [36]. Horng applied the honey bee mating optimization (HBMO) to search for the thresholds of image histogram [38], called maximum entropy honey bee mating optimization (MEHBOT) [38]. Hammouche, Diag, and Siarry compared various meta-heuristic techniques for multilevel thresholding [39]. They found that the differential evolution and the particle swarm optimization were the most effective and the fastest ones.

III. LEVY-FLIGHT FIREFLY ALGORITHM

Fireflies are one of the most special creatures in nature. Fireflies' population estimated around 1900 spices [40]. Most of fireflies produce short and rhythmic flashes and have different flashing behaviour. Fireflies use these flashes for communication and attracting their partner. Firefly Algorithm developed by Xin-She Yang at Cambridge University in 2008 [10].

In the firefly algorithm, there are three idealized rules: (1) all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex.

(2) Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move forward for the brighter one. If there is no brighter than a particular firefly, it will move randomly. (3) The brightness of a firefly is affected or determined by the landscape of the objective function. The pseudo code of these three rules can be shown as Fig. 1.

The distance between any two fireflies i and j at x_i and x_j, is the Cartesian distance.

$$r_{ij} = \| x_i - x_j \| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \qquad (1)$$

As a Firefly's attractiveness is proportional to the light intensity seen by adjacent Fireflies, we can now define the attractiveness β of a Firefly by:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \qquad (2)$$

where, the β_0 is the attractiveness at $r= 0$ and γ is the light absorption coefficient at the source.

If we combine the three idealized rules with the characteristics of l´evy-flights, we can formulate a new l´evy-flight Firefly Algorithm (LFA), which is different from firefly algorithm in movement of fireflies. The movement of a Firefly i, is attracted to another more attractive Firefly j is determined by:

$$X_i = X_i + \beta_0 e^{-\gamma r_{ij}^2}(X_j - X_i) + \alpha sign[rand - \frac{1}{2}] \oplus levy \qquad (3)$$

where, the second term is due to the attraction while the third term is randomization via l´evy-flights with α being the randomization parameter. The product $\oplus$ means entry wise multiplications. The *sign* [*rand – (1/2)*] where, *rand* □ [0, 1] essentially provides a random sign or direction while the random step length is drawn from an l´evy distribution:

$$\text{L´evy} \sim u = t^{-\lambda} \qquad (1<\lambda\leq 3) \qquad (4)$$

which, has an infinite variance with an infinite mean. Here the step of firefly motion is essentially a random walk process with a power-law step-length distribution with a heavy tail.

L´evy-Flight Firefly algorithm
Initialize algorithm parameters:
MaxGen: the maximum number of generations
Objective function of f(x), where x=(x1,........,xd)T
Generate initial population of fireflies or xi (i=1, 2,..., n)
Define light intensity of Ii at xi via f (xi)
While *(t<MaxGen)*
  For *i = 1 to n (all n fireflies);*
    For *j=1 to n (all n fireflies)*
  If *(Ij > Ii), move firefly i towards j; end if*
Attractiveness varies with distance r via Exp[-γr2];
Evaluate new solutions and update light intensity;
    End for j;
  End for i;
Rank the fireflies and find the current best;
End while;
Post process results and visualization;
End procedure;

Figure 1. Pseudo code of the LFA.

IV. THE PROPOSED METHOD

In this section, at first described the entropy measure is described and then details of the proposed segmentation method are explicated.

A. The entropy measure

The entropy criterion, proposed by Kapur et al. [15], has been widely used for determining optimal thresholding in image segmentation [34-38]. The original algorithm has been developed for bi-level thresholding. The method can be also extended to solve multilevel thresholding problems defined as follows.

Let *'L'* be gray-levels in a given image, which in the range {0, 1, 2, ..., *L*-1}. Then one can define, $P_i = h(i)/N$, ($0 \leq i \leq L$-1) where, $h(i)$ denotes the number of pixels with gray-level i, N denotes the total number of pixels in the image.

Here, given that a problem should select c thresholds $\{t_1, t_2, \ldots, t_c\}$ for a given image, the objective function f is to be maximized:

$$f([t_1, t_2, \ldots, t_c]) = H_0 + H_1 + H_2 + \ldots + H_C$$

$$\omega_0 = \sum_{i=0}^{t_1-1} P_i \ , \quad H_0 = -\sum_{i=0}^{t_1-1} \frac{P_i}{\omega_0} \ln \frac{P_i}{\omega_0}$$

$$\omega_1 = \sum_{i=t_1}^{t_2-1} P_i \ , \quad H_1 = -\sum_{i=t_1}^{t_2-1} \frac{P_i}{\omega_1} \ln \frac{P_i}{\omega_1}$$

$$\omega_2 = \sum_{i=t_2}^{t_3-1} P_i \ , \quad H_2 = -\sum_{i=t_2}^{t_3-1} \frac{P_i}{\omega_2} \ln \frac{P_i}{\omega_2} \quad ,\ldots.$$

$$\omega_c = \sum_{i=t_c}^{t_c-1} P_i \ , \quad H_c = -\sum_{i=t_c}^{t_c-1} \frac{P_i}{\omega_c} \ln \frac{P_i}{\omega_c}. \qquad (5)$$

In the proposed MELFA algorithm, there was an attempt to obtain this optimum c-dimensional vector $[t_1, t_2, \ldots, t_c]$, which can maximize the entropy. The higher the value of the objective function, the more centralized distribution would be expected to be produced for each histogram-based segmented region of the image.The objective function was also used to act as the fitness function for the proposed algorithm.

B. The proposed MELFAT method

In this paper, a new method was proposed based on the entropy measure optimized by LFA. Vector-dimension number depended on the number of thresholds used in segmentation. Upon initialization, the fireflies were randomly spread over the whole plan. At the same time the entropy measure was obtained for each corresponding firefly and the maximum value was found. Subsequently, the fireflies' fitness and position were updated according to the firefly algorithm.

The details of the MELFAT algorithm could be introduced as follows:

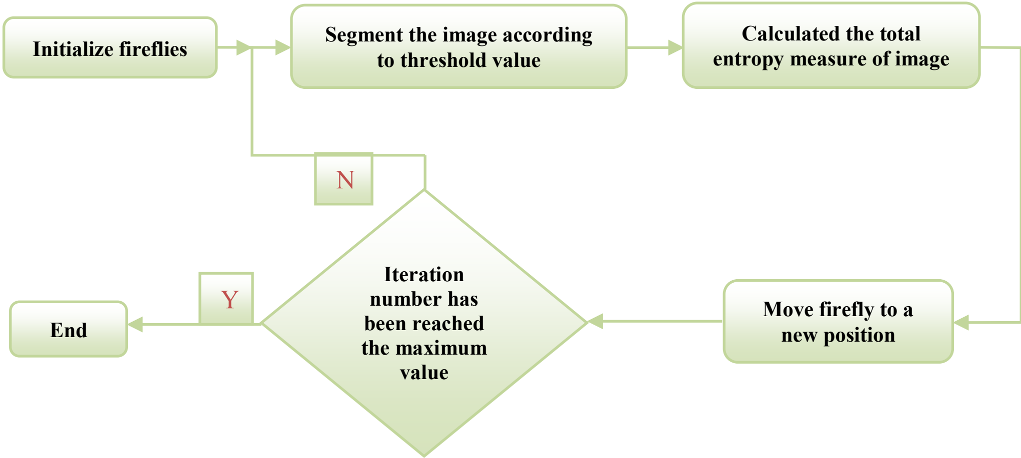

Figure 2. Flowchart of Proposed Segmentation Method.

Step1: Initialize fireflies with random thresholds and set LFA parameters according to [10].

Step2: Segment the image according to the threshold value.

Step3: Calculate the total entropy of image according to (5).

Step4: Move firefly to a new position; consider maximizing the entropy measure of image and updating the fireflies' position and fitness.

Step5: Check if the iteration number has breached the maximum value. If so, deduction ends; otherwise, jump to Step 2.

Step6: Finally, images are segmented by optimal thresholds.

The flowchart of the proposed algorithm is shown in Fig. 2.

The evaluate segmentation results, the uniformity measure was applied.

$$U = 1 - 2 \times c \times \sum_{i=0}^{c} \sum_{i \in R_i} (f_i - \mu_j)^2 / N / (f_{\max} - f_{\min})^2 \quad (6)$$

where, c, number of thresholds. R_j, jth segmented region, N, total number of pixels in the given image gray level of pixel i, f_i, gray level of pixel i, μ_j, mean gray level of pixels in jth region, f_{max}, maximum gray level of pixels in the given image, f_{min}, minimum gray level of pixels in the given image.

The value of this uniformity measure, U, should be a positive fraction .In other words, it should lie between 0 and 1. A higher value of u indicates that there is better uniformity in the thresholded image, depicting better quality of thresholding. On the other hand, a lower value of u indicates the worse quality of the thresholding procedure.

V. EXPERIMENTAL RESULTS

In this section first, the LFA parameters and particle presentation were described; then, the details of the proposed method were demonstrated by experimental results.

A. *Particle representation*

The performance of LFA depends on many factors. According to the standard LFA, in this implementation, β_0=1 and α□ [0, 1] can be assumed. Rand is a random number generator uniformly distributed in [0, 1] and λ=1.5. The parameter γ characterizes variation of the attractiveness, and its value is important for determining the speed of the convergence and how the FA behaves. In most applications, it typically varies from 0.01 to 100. In this paper γ=1 was set. The population size was set at 20. The fireflies was initialized as a gray value intra the intervals of (0 ~ 255) and the largest truncated generation was 30. The dimension of input vectors depended on the number of threshold used for segmentation. In this paper, different threshold numbers, from were used 1 to 5 for segmentation.

B. *MELFAT results*

The proposed algorithm was tested on 'Lena', 'Peppers', 'Bird', 'Cameraman' and 'Gold hill '. These original test images and their histograms are shown in Fig. 3. The performance metrics for checking the effectiveness of the method were chosen as the uniformity measure. Also the performance of the proposed scheme was compared with the results of Gaussian smoothing (Lim, Y. K., & Lee, S. U. (1990)), Symmetry-duality method (Yin, P. Y., & Chen, L. H. (1993)), improved GA-based algorithm (Yin, P. -Y. (1999)), the hybrid cooperative-comprehensive learning based PSO algorithm (HCOCLPSO) (Maitra, M., & Chatterjee, A. (2008)) and a new social and momentum component adaptive PSO algorithm (SMCAPSO) (Chander, A.,& Chatterjee, A.,& Siarry, P.(2011)). As demonstrated by these methods through considering two popular

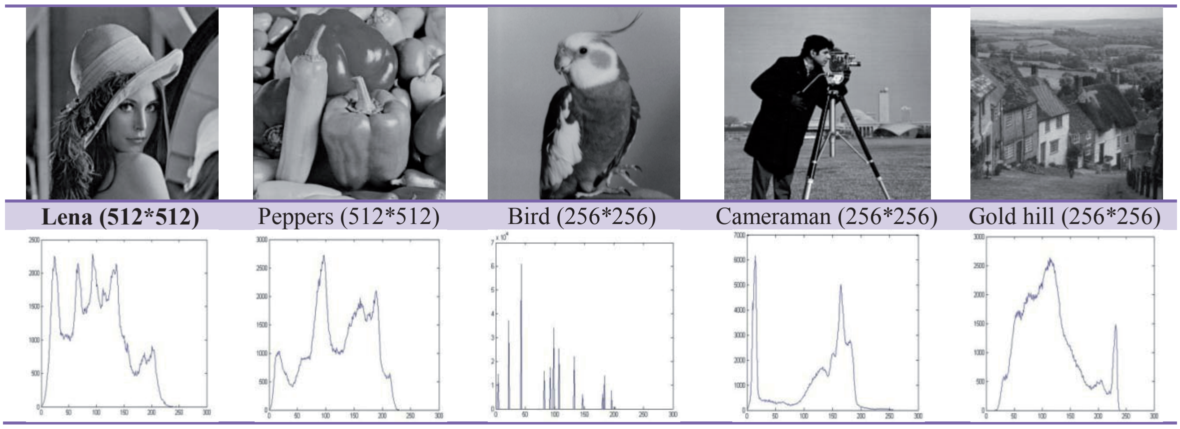

Figure 3. The test images and corresponding histograms: (a) 'Lena', (b) 'Peppers', (c) 'Bird', (d) 'Cameraman' and (e) 'Gold hill '.

images, 'Lena' and 'Peppers' (each with the size of 512□512), these two images were chosen to present comparative results.
Table 1 shows the selected thresholds, uniformity value and the corresponding fitness value of five test images with different thresholds. As can be seen, with increasing the number of thresholds, the amount of objective values and uniformity measures increase in all cases. For example, in 'Lena' image for $c = 2$, the uniformity measure was 0.9824 and objective value is 12.43, respectively. Moreover; for c=5, the uniformity measure and uniformity increased to 0.9927 and 23.00, respectively. It was demonstrated that with increasing the number of thresholds, image would get separated to smoother regions.

Table 1. Thresholds, values and fitness values for test images by using MELFAT algorithm

Image	*c*	*Threshold*	*Uniformity*	*Objective value*
*Lena (512*512)*	2	59-116	0.9824	12.43
	3	47-108-156	0.9828	15.68
	4	70-91-126-238	0.9832	21.70
	5	64-96-128-215-238	0.9927	23.00
*Peppers (512*512)*	2	72-142	0.9892	12.65
	3	62-107-154	0.9893	15.71
	4	70-139-160-190	0.9893	18.88
	5	49-108-162-191-210	0.9894	22.00
*Bird (256*256)*	2	106-131	0.9804	11.61
	3	39-57-130	0.9861	14.28
	4	50-113-125-188	0.9881	19.50
	5	81-106-173-205-232	0.9905	20.00
*Camera (256*256)*	2	120-192	0.9919	12.22
	3	26-122-201	0.9917	15.14
	4	84-128-174-217	0.9939	20.85
	5	63-120-148-246	0.9942	23.00
*Gold hill (256*256)*	2	84-153	0.9842	12.51
	3	72-119-166	0.9872	15.53
	4	76-117-163-232	0.9872	19.27
	5	90-115-147-219-242	0.9866	19.31

The fitness values of MELFAT, HCOCLPSO and GA Learning-kapur algorithms are shown in Table 2. According to the corresponding fitness values of MELFAT algorithm, the effectiveness of the proposed segmentation algorithm can be found. The objective values mentioned to entropy measure, the higher the value of the objective function; the more centralized distribution would be expected to be produced for each histogram-based segmented region of the image. In HCOCLPSO method, the objective values of 'Lena' image for different values of c=2, 3, 4 and 5 were 12.35, 15.31, 17.99 and 20.54 respectively. In the GA learning approach, the slightly different objective values were 12.10, 14.99, 17.60 and 20.12, however in the proposed thresholding method, the amount of objective values increased in all the cases. It indicates that the capability of LFA for finding optimal thresholds depends on MET measure. The overall results showed that the proposed regimentation approach; give better results in comparison with two other well-known methods.

Table 2. A comparative study of objective values for MELFAT, HCOCLPSO, GA Learning-kapur algorithms

Images	*c*	MELFAT	HCOCLPSO	GA Learning
Lena (512*512)	2	12.43	12.35	12.10
	3	15.68	15.31	14.99
	4	21.70	17.99	17.60
	5	23.00	20.54	20.12
Peppers (512*512)	2	12.65	12.64	12.39
	3	15.71	15.70	15.36
	4	18.88	18.49	18.08
	5	22.00	21.28	20.84

Figure 4. The thresholded images of 'Lena', 'Peppers', 'Bird', 'Cameraman' and 'Gold hill' using proposed method, 2-5 level thresholds.

Table 3, reveals the comparison of the uniformity measures obtained using four methods for the same 'Lena' and 'Pepper' images. It can be seen that the proposed MELFAT could achieve significantly better segmentation results compared with other methods, as demonstrated by quite higher values of uniformity in each case. They could achieve the uniformity value in the range of 0.9824 to 0.9927 while other methods failed to even reach the uniformity value of 0.9843. Also, for the visual interpretation of the segmentation results, the segmented 'Lena', 'Peppers', 'Bird', 'Cameraman' and 'Gold hill ' images with c = 2, 3, 4 and 5 and their corresponding thresholds were presented in Fig. 4 respectively. These figures reveal that thresholded images are much smoother and more uniform with increasing the number of thresholds. Consequently, they resemble the original image more closely for a higher number of levels. This visual interpretation is in conformation with the quantitative results reported in Table 2 and 3. So, it can be stated that, with the higher number of thresholds, the quality of segmented images got superior for the multilevel thresholding employing MELFAT algorithm. The obtained threshold values could correctly separate the corresponding region.

Table 4 shows the selected thresholds of the two test images in comparison with three other methods. As is shown in Table 3, the uniformity measures of

Gaussian smoothing, symmetry duality and GA learning methods in c=5 for 'Lena' and 'Peppers'

Table 3. A comparative study of uniformity for MELFAT, SMCAPSO, HCOCLPSO, GA Learning-kapur, Gaussian smoothing method and symmetry duality method algorithms.

Image	c	MELFAT	HCOCLPSO	SMCAPSO	GA Learning	Gaussian smoothing	symmetry duality
Lena (512*512)	2	0.9824	0.9682	0.9694	0.8844	0.7782	0.8174
	3	0.9828	0.9760	0.9587	0.9164	0.8752	0.8476
	4	0.9832	0.9792	0.9541	0.9198	0.9143	0.9223
	5	0.9927	0.9799	0.9843	0.9269	0.9062	0.9277
Peppers (512*512)	2	0.9893	0.9647	0.9565	0.8659	0.8485	0.8494
	3	0.9892	0.9728	0.9768	0.8970	0.8713	0.8702
	4	0.9892	0.9738	0.9739	0.9054	0.8386	0.8371
	5	0.9894	0.9779	0.9733	0.9080	0.8802	0.8771

Table 4. A comparative study of optimal thresholds for MELFAT, SMCAPSO, HCOCLPSO, GA Learning-kapur algorithms

Image	c	MELFAT	HCOCLPSO	SMCAPSO	GA Learning
Lena (512*512)	2	59-116	100-166	116-166	105-176
	3	47-108-156	79-125-176	116-166- 190	90-131-176
	4	70-91-126-238	74-114-149-186	116-140-166-190	75-105-143-181
	5	64-96-128-215-238	69-104-137-169-197	75-116-140-166-190	74-103-133-166-195
Peppers (512*512)	2	72-142	75-145	119-165	84-150
	3	62-107-154	62-113-166	62-119-165	72-119-167
	4	70-139-160-190	46-80-126-172	62-119-165-187	57-90-132-174
	5	49-108-162-191-210	43-78-118-154-193	62-119-143-165-167	56-88-121-157-194

images were not good enough, indicating that the threshold values of the mentioned methods were not good and they could not separate pixels in proper segments. The results of HCOCLPSO and SMCAPSO methods were better in comparison with other three methods and their results in the case of c=5 for 'Lena' image were 0.9799 and 0.9843 and for 'peppers' image were 0.9770 and 0.9733 respectively. The experimental results showed that the results of MELFAT method also outperformed these two methods for different images and the calculated uniformity value for 'Lena' and 'peppers' were 0.9927 and 0.9894, respectively. Thus, the capability of the proposed method for finding optimal threshold values was shown. The proposed approach could separate pixels in smoother region and increase the performance of image segmentation results.

VI. CONCLUSION

In this paper, an optimal multilevel thresholding algorithm employed in l´evy-flight firefly algorithm was described. The MELFAT algorithm simulated the behavior of firefly in developing an algorithm to select the optimal thresholds for the maximum entropy based image segmentation. The MELFAT algorithm was employed for several benchmark images, which could demonstrate significant enhancement in performance compared with several other popular contemporary methods. The accuracy of image segmentation was evaluated through the uniformity measure and objective value. It was also demonstrated that, with increasing the number of thresholds, the regions separated more smoothly and an increase happened in the performance of the results of image segmentation. Comparisons with other thresholding methods, symmetry duality, Gaussian smoothing, GA Learning and HCOCLPSO showed that the proposed method determined optimal threshold values, which proved. It proves the capability of LFA in finding optimal thresholds with respect to the MET measure. As far as future works are concerned, this method can be used for the segmentation of some different images like medical image or color images.

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