A Competitive Swarm Algorithm for Image Segmentation Guided by Opposite Fuzzy Entropy

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***Abstract*—This paper proposes an alternative multilevel thresholding (MLT) image segmentation method by improving the behavior of the grasshopper optimization algorithm (GOA). This is achieved by using the operators of the sine-cosine algorithm (SCA) to work in a competitive manner with the operators of traditional GOA. This will lead to enhance the quality of the solutions during the updating process that will affect the convergence of the proposed GOASCA towards the global solution. In addition, the proposed GOASCA aims to minimize the difference between the fuzzy entropy and its opposite fuzzy entropy that is used as a fitness function to evaluate the quality of the solution. This objective function gives the GOASCA to explore the whole search space. To assess the quality of the obtained threshold values by GOASCA, a set of eight images are used which have different characteristics. Moreover, the results of GOASCA are compared with a set of well-known MLT image segmentation approaches, and these results have shown the high quality of GOASCA to segmented the image, as well as, shown that the current objective function provides results better than the traditional fuzzy entropy in terms of the performance measures of image segmentation.**

***Index Terms*—Opposite fuzzy set; Image segmentation; Grasshopper optimization algorithm; Sine-cosine algorithm.**

I. INTRODUCTION

In recent years, image segmentation methods received more attention since they established their performance in different applications as a pre-processing step. For example, medical diagnosis [1], agricultural [2] and satellite image processing [3]. The main aim of any image segmentation method is to divide the image into different sets of groups with similar information such as texture, contrast, gray level, brightness, and color.

There are several image segmentation techniques have been applied including edge detection [4], clustering algorithms [5], threshold segmentation [6], and region extraction [7]. Meanwhile, the thresholding techniques are the most used segmentation methods since they provide better results and are easier to implement than other approaches. The thresholding image segmentation methods can be classified into two categories, the bi-level, and multi-level segmentation. In the bi-level group, the image is segmented into two classes, while, the multi-level category aims to split the image into a different number of classes (more than two) [5]. Since, the images in most of the real-world applications contain objects divided into more than two groups, the bi-level thresholding image segmentation methods become unsuitable. Therefore, the multilevel thresholding (MLT) techniques have been used wider than bi-level methods.

Most of the image segmentation based on MLT methods use the image histogram as an input to determine the thresholds by maximizing/minimizing the objective functions, for example, fuzzy entropy, Kapur's entropy, Renyi entropy, and Otsu's variance. However, the traditional MLT methods suffer from some limitation such as they require more computational time to determine the suitable threshold values. To address these issues, several meta-heuristic (MH) methods have been applied such as, the firefly optimization algorithm (FA) [8], harmony search (HS) algorithm [9], honey bee mating optimization (HBMO) [10], artificial bee colony (ABC) [11], whale optimization algorithm (WOA) [12], and moth-flame optimization (MFO) [13].

Ahmadi et al. [14] developed an MLT method by using a modified bird mating optimization (BMO). This algorithm uses the differential evolution (DE) to improve the segmentation process and it has been assessed using eight images. This approach established its performance over other methods. Chakraborty et al. [15] applied the enhanced elephant herding optimization (EHO) to find the threshold values by combining

978-1-7281-6932-3/20/$31.00 ©2020 IEEE

EHO with the dynamic Cauchy mutation (DCM), as well as using the opposite-based learning (OBL) to improve the performance of solutions. Mousavirad et al. [16] presented the Human Mental Search (HMS) as MLT method and used the Otsu and Kapur as fitness functions to assess the quality of the solutions. Chakraborty et al. [17] introduced a modified particle swarm optimization (PSO) named IPSO to determine the threshold values using the minimum cross-entropy as a fitness function. This algorithm is applied to grayscale images and its performance is better than the other methods including PSO, cuckoo search (CS), ABC, and GA. Elaziz et al. [13] proposed the whale optimization algorithm (WOA) and the moth-flame optimization (MFO) as MLT image segmentation and used the Otsu as fitness function and the results established the high performance of the MFO over the WOA. Also, a modified salp swarm algorithm (SSA) based on MFO is proposed in [18] to improve the performance of the segmentation and used fuzzy entropy as a fitness function to evaluate the quality of solutions. There are several other MLT image segmentation techniques [19]–[21]. However, these methods have some limitations that can affect the quality of the segmentation process. These limitations result either from the problems of MH methods such as stagnation at local optima since they don't have a good balance between exploration and exploitation. In addition, the limitations come from the fitness function itself. This motivated us to develop an alternative MLT technique based on the concept of the fuzzy opposite set [22] and the competitive behavior between the grasshopper optimization algorithm (GOA) [23] and sine-cosine algorithm (SCA) [24].

In general, the GOA [23] is MH which simulates the behavior of grasshopper and it has been applied to several applications according to this simulation. For example, renewable energy [25], among others [26], [27]. Moreover, the SCA [24] that is considered as mathematical-based MH techniques uses the two mathematical functions called sine and cosine to update the solutions. SCA is applied to different fields including Breast Cancer Classification [28], Economic and emission dispatch problems [29] and others [30].

In addition, the opposite fuzzy set (OFS) [22] is applied to determine the threshold value to segment the image according to finding the opposite value for the parameters of the membership function. Using the concept of OFS reduces the uncertainties unlike the other methods that don't depend on the opposition to have a degree of certainties.

The proposed GOASCA MLT image segmentation starts by determining the parameters such as a number of solutions and the maximum number of iterations, followed by receiving the image and calculate its histogram. Thereafter, a set of agents is generated which have integer values depending on the value of the histogram. then the quality of each agent will be evaluated using the difference between the fuzzy entropy and its opposite, followed by determining the best solution which has the smallest fitness value. The next step is to update the solutions using either the operators of GOA or SCA according to the probability of the fitness value for each agent. The steps of updating the agents are repeated until reaching the maximum number of iteration that used as stop conditions. The output of the proposed GOASCA is the best solution that represents the threshold values that will be used to segment the image. To the authors' knowledge, no other works have been introduced to improve the GOA by using the operators of SCA nor any image segmentation technique based on MH method used the difference between the fuzzy entropy and its opposite as fitness function yet.

The main contribution of the current study can be summarized as follows:

1) Develop an alternative multilevel image segmentation method based on improving the grasshopper optimization algorithm (GOA).
2) Enhance the performance of the GOA by using the SCA in a competitive manner.
3) Develop fitness function based on the fuzzy entropy and its opposite value for evaluate the quality of each agent inside the population.
4) Evaluate the quality of GOASCA using eight images and compare them with a set of other image segmentation approaches.

The structure of the rest sections of the paper is as follows. In Section II, the description of the basic information about the MLT problem, GOA, and SCA are introduced. Section III introduces the proposed GOASCA approach. Section IV introduces the experiment and the discussion of the results. Finally, Section V concludes the paper and presents some of the future works.

II. BACKGROUND

A. Definition of MLT Problem

In this section, the definition of the MLT problem is introduced by assuming the image I has a set of $K+1$ groups and the main objective of the MLT approach is to find a set of K threshold values that split I into its group. This can be formulated using the following equation:

$$\begin{aligned} C_0 &= \{I_{ij} \mid 0 \leq I_{ij} \leq t_1 - 1\}, \\ C_1 &= \{I_{ij} \mid t_1 \leq I_{ij} \leq t_2 - 1\}, \\ &\dots \\ C_K &= \{I_{ij} \mid t_K \leq I_{ij} \leq L - 1\} \end{aligned} \tag{1}$$

where $C_k, k = 1, 2, ..., K$ represents the k-th group if image I, while the gray value is given by I_{ij} and L refers to the maximum gray value of I. Therefore, the MLT problem is given as in Eq. (2) which considered as minimizing optimization problem

$$t_1^*, t_2^*, ..., t_K^* = \arg\min_{t_1,...,t_K} Fit(t_1, ..., t_K) \tag{2}$$

Fit is the objective function and there are several functions can be used, however, we used the concept of opposite fuzzy set to form the objective function and it is defined in the following section.

B. Opposite Points and Opposite Fuzzy Sets

Let $X = [x_1, x_2, ..., x_n]$ be a point in an n-dimensional space, where $x_i \in [X^i_{min}, X^i_{max}] \in R$. The type-I opposite point $\overline{X} = [\overline{x}_1, ..., \overline{x}_n]$ is then completely defined where [22]:

$$\overline{x}_i = X^i_{max} + X^i_{min} - x_i \tag{3}$$

The set $\overline{A}$ with membership function $\mu_{\overline{A}}(x) = f(x; \overline{\alpha}, \overline{\sigma})$ is type I opposite of the set A with membership function $\mu_A(x) = f(x; \alpha, \sigma)$, if $\overline{\alpha}$ and $\overline{\sigma}$ are type I opposites of α and σ. respectively.

C. Objective function

In this section, we will formulate the objective function according to the Opposite Fuzzy Sets (OFS). In this study, the OFS will depend on the fuzzy entropy and it opposite. In general, the fuzzy entropy is defined as in Eq. (4) [31]:

$$Fit_{FE}(t_1, ..., t_K) = \sum_{k=1}^{K} H_i \tag{4}$$

$$H_k = -\sum_{i=0}^{L-1} \frac{p_i \times \mu_k(i)}{P_k} \times ln(\frac{p_i \times \mu_k(i)}{P_k}),\ P_k = \sum_{i=0}^{L-1} p_i \times \mu_k(i) \tag{5}$$

$$\mu_1(l) = \begin{cases} 1 & l \le a_1 \\ \frac{l-c_1}{a_1-c_1} & a_1 \le l \le c_1 \\ 0 & l > c_1 \end{cases}, \tag{6}$$

$$\mu_K(l) = \begin{cases} 1 & l \le a_{K-1} \\ \frac{l-a_K}{c_K-a_K} & a_{K-1} < l \le c_{K-1} \\ 0 & l > c_{K-1} \end{cases} \tag{7}$$

In Eq. (7), the fuzzy parameters are given by $a_1, c_1, ..., a_{k-1}, c_{k-1}$ and $0 \le a_1 \le c_1 \le ... \le a_{K-1} \le c_{K-1}$. The threshold $t_k = \frac{a_k + c_k}{2}, k = 1, 2, ..., K-1$.

Therefore, by applying type I opposite to Eq. (4), we will obtain the opposite fuzzy entropy Fit_{OFE} and the objective function is defined as in Eq. (8) which represents the difference between Fit_{FE} and Fit_{OFE}.

$$Fit_G = |Fit_{OFE} - Fit_{FE}| \tag{8}$$

where $|.|$ represents the absolute value of the distance between the two functions.

D. Grasshopper Optimization Algorithm

Saremi et al. [23] adapted the life cycle of the grasshopper pests as an inspiration for his new optimizer algorithm named Grasshopper Optimization Algorithm (GOA). The natural development of the grasshoppers' life passes by three stages first is an egg then a nymph and finally an adulthood. The features of grasshoppers in each stage are different, where they jump and move in rolling cylinders with small steps and slow movement, besides eating all the vegetables/fruits that found in their way in the nymph phase. While grasshoppers tend to fly for a long distance in a swarm with an abrupt movement in the adulthood age. These features can be modeled mathematically by accounting the location of Grasshopper $(X_i, i = 1, 2, \ldots, N)$ as [23]:

$$X_i = S_i + G_i + A_i, \tag{9}$$

where S_i represents the social interaction of X_i and it is formulated as:

$$S_i = \sum_{j=1, i \ne j}^{N} s(d_{ij}) \widehat{d}_{ij}, \qquad d_{ij} = |X_i - X_j| \tag{10}$$

where d_{ij} denotes the distance between the ith and jth solutions; the s illustrates the strength of social forces function and it is determined as:

$$s(y) = fe^{\frac{-y}{l}} - e^{-y} \tag{11}$$

In Eq. (11), l and f are the attractive length scale and intensity of attraction, respectively. In Eq. (9), the G_i and A_i indicate wind advection and the gravity force of X_i, respectively and are determined as [23]:

$$G_i = -g\widehat{e}_g, \qquad A_i = u\widehat{e}_w \tag{12}$$

where g and u are constant values of the gravitational and drift, respectively; whereas e_w and e_g are the direction of the wind and the unity vector towards the center of the earth respectively. Followed [23], Eq. (9) cannot be used directly and it is reformulated as in Eq. (13)

$$X_i = c(\sum_{j=1, i \ne j}^{N} c\frac{ub - lb}{2} s(|X_j - X_i|) \frac{X_j - X_i}{d_{ij}}) + \widehat{T}_d \tag{13}$$

where ub and lb are the low and the high boundaries; while T_d is the value of the best solution obtained so far. However, in Eq. (13), the authors assumed that the gravity and the wind direction are always considered towards T_d. The c is a decreasing coefficient to shrink the comfort zone, repulsion zone, and attraction zone as:

$$c = c_{max} - t\ \frac{c_{max} - c_{min}}{t_{max}} \tag{14}$$

where $c_{min} = 0.00001$ and $c_{max} = 1$ are the minimum value and the maximum value of c, respectively. The t and t_{max} refer to the current generation, and the total number of generation, respectively.

The steps of the GOA is illustrated in Algorithm 1.

Algorithm 1 The GOA Algorithm [23]

```
Initialize the value of the parameters such as population size (N),
  c_max, c_min, and maximum number of iteration (t_max)
Generate a random population (X)
Set the current iteration t = 1
while (t < t_max) do
    Compute the fitness function f
    Select the best solution T̂_d
    Update the value of c using Eq.(14)
    for i = 1 : N do
        Normalize the distance between the solutions in X in the interval
          [1,4].
        Update X_i ∈ Z using Eq.(13)
    end for
    t = t + 1
end while
Return T̂_d.
```

E. Sine-Cosine Algorithm

The trigonometric functions, especially sine and cosine ones, are the core of the Sine-Cosine Algorithm where Mirjalili et al. in [24] used the features of these functions to achieve optimal solutions for regarding optimization problems. SCA likes other the meta-heuristic algorithms starts by generating a random population X with N solutions and each X_i has dimension D_X. Then based on these solutions, the objective function Fit_i for X_i is computed and the best solution X_b is deduced according to the best Fit_b. Subsequently, the solutions are modified via following the main structure of SCA that can be represented by the following equations:

$$X_i = \begin{cases} X_i + \gamma_1 \times sin(\gamma_2) \times |\gamma_3 z_b - X_i| & if\ \gamma_4 < 0.5 \\ X_i + \gamma_1 \times cos(\gamma_2) \times |\gamma_3 z_b - X_i| & if\ \gamma_4 \geq 0.5 \end{cases} \tag{15}$$

where $|.|$ and $\gamma_i \in [0,1], i = 1,2,3,4$ represent the absolute value, and random variables, respectively. The γ_2 is applied to find the next movement of X_i outward (or toward) X_b. While, γ_1 targets to achieve a smooth harmonization between the exploitation and the exploration and it is updated during the optimization using the following equation [24]:

$$\gamma_1 = \sigma - t\frac{\sigma}{t_{max}} \tag{16}$$

where σ represents a constant. The SCA aforementioned steps are repeated until achieving the termination criteria. The final steps of SCA are discussed in Algorithm 2.

Algorithm 2 The SCA Algorithm

1: Generate a set of N random solutions which have dimension D_X.
2: **while** $(t < t_{max})$ **do**
3: Calculate the fitness value Fit for each solution.
4: Find the best solution X_b that has Fit_b.
5: generate random variables $\gamma_i, i = 1,2,3,4$.
6: Using Eq. (20) to update each solution.
7: **end while**
8: Output: The best solution X_b.

III. Proposed GOASCA Method

The framework of the proposed MLT image segmentation approach based on a competitive swarm algorithm is given in Fig. 1. In the proposed method, the SCA is used to enhance the convergence of the GOA towards the global solution. This achieved by using the operators of the two techniques in competition scenario through updating the solutions using either the operators of GOA or SCA according to the probability of the fitness value. The proposed GOASCA MLT image segmentation method has four phases which are illustrated in the following sections with more details.

A. Initial phase

The GOASCA starts by computing the histogram of image I and using this information to form the search space for the agents. Then the initial value for a set of N agents (X) is constructed using Eq. (17):

$$X_i = floor(lb_i + \alpha_i \times (ub_i - lb_i)),\ i = 1,2,...,N \tag{17}$$

where $\alpha_i \in [0,1]$ refers to a random number, while $lb_i = 0$ and $ub_i = 255$ are the boundaries of the search domain,

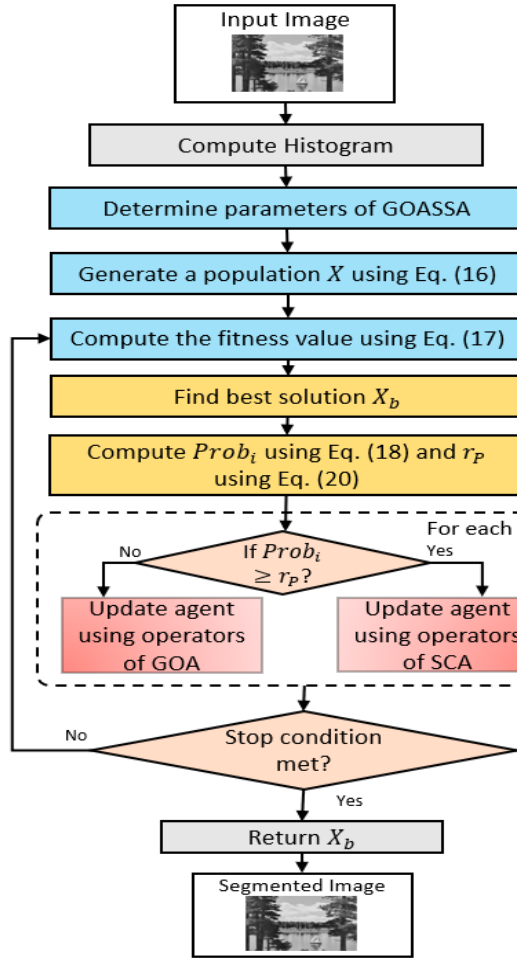


Fig. 1: The Framework of GOASCA method.

respectively. $floor(x)$ is used to find the integer value of x since the threshold value is integer value.

B. Evaluating phase

This phase begins by computing the fitness value of each agent X_i this performed through two steps. Firstly, compute the Fuzzy entropy (Fit_{FE}) as defined in Eq. (4). Secondly, Compute the opposite of fuzzy entropy (Fit_{OFE}) by computing the opposite for the current solution X_i which represents the parameters of the membership function. Followed by compute the difference between Fit_{OFE} and Fit_{FE} which considered the main objective (Fit_G) used in this study as defined in Eq. (8).

C. Updating phase

This phase starts by determining the best agent (X_b) which has the smallest fitness value (Fit_G^b). Next, the probability of each agent is computed using the following equation.

$$Prob_i = \frac{Fit_G^i}{\sum_{i=1}^{N} Fit_G^i} \tag{18}$$

Thereafter, the operators of the SCA will be used to update the current agent when the value of $Prib_i \leq r_P$, otherwise, the operators of GOA will be used. This process can be formulated as:

$$X_i = \begin{cases} SCA & if\ Prob_i < r_P \\ GOA & otherwise \end{cases} \tag{19}$$

$$r_p = min_{Prob} + r_1 \times (max_{Prob} - min_{Prob}),\ r_1 \in [0,1] \tag{20}$$

where min_{Prob} and max_{Prob} represents the minimum and maximum value, respectively, of the $Prob$.

D. Terminal phase

The steps of the two previous phases (i.e., evaluating and updating) are performed again until the stop conditions are reached. The proposed method uses the total number of iterations as stop condition to evaluate the quality of the segmented image using the obtained best solution X_b.

IV. EXPERIMENT

A. Dataset Description

In this section, the information about a set of eight images that will be used to assess the quality of the proposed method is introduced. These images have different characteristics and this observed from the histogram of each image as given in Fig. 2.

B. Performance Measures

The quality of the segmented image using the threshold values that obtained by the proposed method is evaluated using a set of metric including the Peak-to-noise-ratio (PSNR), and Structural Similarity Index (SSIM).

1) PSNR: This metric is used to compute the difference between I and its segmented image $Iseg$ as formulated in Eq . (21).

$$PSNR = 20log_{10}(\frac{255}{RMSE}),\quad (in\, dB) \tag{21}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(I_{ij} - Iseg_{ij})^2}{N \times M}} \tag{22}$$

where M and N are the number of rows and columns of I, respectively.

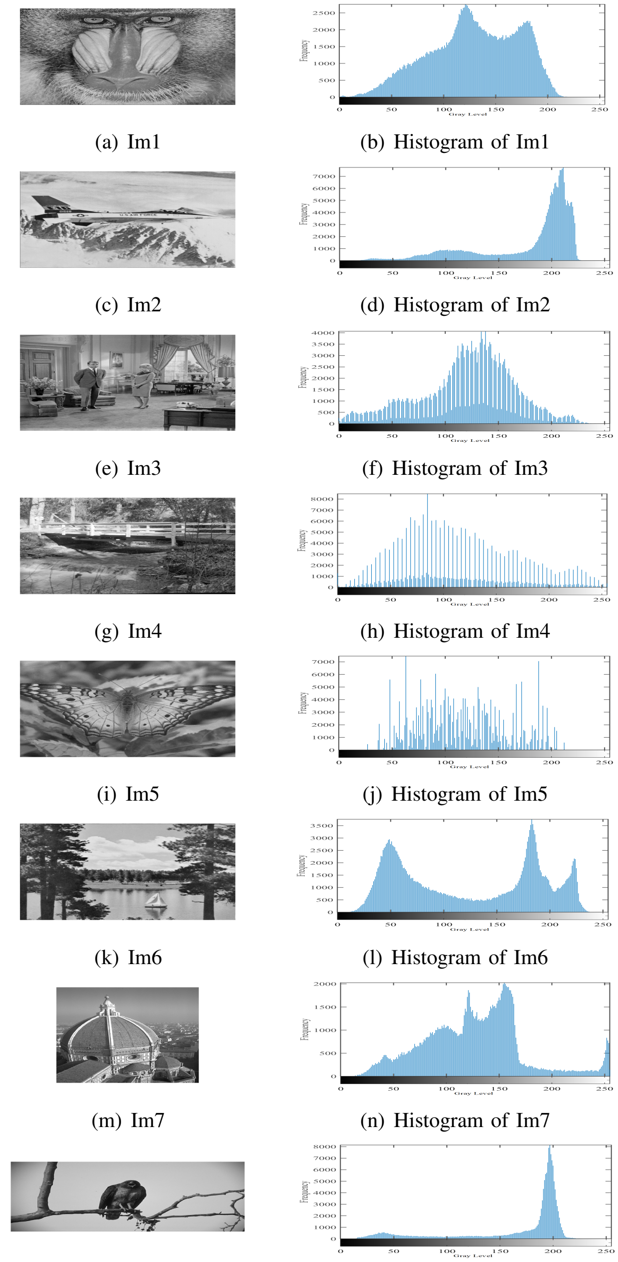
2) SSIM: This measure used to find the similarity between I and $Iseg$. and it is formulated as:

$$SSIM(I, Iseg) = \frac{(2\mu_I\mu_{Iseg} + c_1)(2\sigma_{I,Iseg} + c_2)}{(\mu_I^2 + \mu_{Iseg}^2 + c_1)(\sigma_I^1 + \sigma_{Iseg}^2 + c_2)}, \tag{23}$$

where μ_I (μ_{Iseg}) and $\sigma_I(\sigma_{Iseg})$ refer to the mean intensity and the standard deviation of $I(Iseg)$, respectively. While the covariance of $Iseg$ and I is given by $\sigma_{I,Seg}$. The value of $c_1 = 6.5025$ and $c_2 = 58.52252$.

TABLE I: Parameters setting.

Algorithm	Parameters
GWO	$a \in [2, 0]$
GOA	$c_{max} = 1$, $c_{min} = 0.00004$
SCA	$a = 2$
CS	Nests no. = 20 , $P_a = 0.25, \beta = 1.5$



(a) Im1 (b) Histogram of Im1
(c) Im2 (d) Histogram of Im2
(e) Im3 (f) Histogram of Im3
(g) Im4 (h) Histogram of Im4
(i) Im5 (j) Histogram of Im5
(k) Im6 (l) Histogram of Im6
(m) Im7 (n) Histogram of Im7
(o) Im8 (p) Histogram of Im8

Fig. 2: Tested images and their histograms.

C. Results and Discussion

In this section, the performance of the proposed GOASCA is compared with four algorithms including CS, grey wolf optimization (GWO), GOA and SCA. The parameter seeting for each algorithm is given in Table I.

The comparison results according to the OFS and fuzzy entropy are given in Tables II-III and they performed using three different threshold levels (i.e., 8, 17, and 19). These values are used since they represent high level of threshold and to assess the quality of the obtained solution. It can be noticed from Table II which depicts the PSNR value for each method depends on the two objectives functions the following

TABLE II: PSNR

K		OFS					Fuzzy Entropy				
		CS	GWO	GOASCA	GOA	SCA	CS	GWO	GOASCA	GOA	SCA
8	Im1	18.34	**18.89**	18.47	18.54	15.12	**18.15**	17.71	17.78	17.05	14.99
	Im2	18.46	**19.06**	18.93	18.16	17.86	15.72	15.96	15.37	14.91	**16.73**
	Im3	**19.30**	17.51	18.97	17.09	12.76	**17.70**	17.06	17.12	16.78	13.05
	Im4	**18.74**	18.14	17.77	18.52	11.36	16.01	**16.16**	15.91	15.75	15.31
	Im5	18.05	18.09	**19.18**	18.94	16.31	15.18	15.22	**15.58**	14.07	15.04
	Im6	**18.93**	18.56	18.79	17.81	15.21	**16.00**	15.54	15.89	15.14	13.30
	Im7	18.35	17.67	**18.86**	17.72	15.62	15.15	**16.90**	16.64	14.71	15.07
	Im8	17.99	17.50	**18.57**	17.85	13.70	15.50	15.42	**15.57**	14.24	15.10
17	Im1	24.13	22.70	**24.41**	23.52	17.96	22.53	23.07	**23.93**	22.32	16.76
	Im2	24.67	**25.20**	24.10	24.58	17.87	21.33	20.66	**22.32**	20.90	16.96
	Im3	24.03	**24.11**	23.93	23.30	16.63	**22.89**	22.49	22.32	20.98	15.19
	Im4	23.16	23.20	**24.08**	23.60	19.16	22.68	**22.87**	22.60	20.37	15.58
	Im5	23.08	**24.41**	24.10	23.63	18.51	22.21	22.16	**22.23**	19.23	16.43
	Im6	23.24	22.99	**23.76**	22.93	18.13	**22.61**	21.41	20.69	20.15	14.71
	Im7	**23.93**	23.37	22.87	23.51	18.88	22.68	22.89	**22.96**	19.94	15.90
	Im8	**24.30**	23.03	24.28	23.34	15.90	18.70	19.36	**20.33**	18.92	15.47
19	Im1	24.17	24.03	**24.66**	23.85	20.00	23.24	**24.25**	23.57	23.08	16.74
	Im2	24.87	**25.47**	24.97	24.90	14.85	22.74	21.79	**23.37**	21.58	18.02
	Im4	**24.61**	24.30	24.56	24.19	21.02	**23.71**	21.91	22.66	21.44	16.02
	Im5	24.29	24.21	24.45	**24.50**	21.93	21.15	22.94	**23.86**	21.75	15.23
	Im6	24.62	24.07	**24.90**	23.46	18.35	21.85	**23.62**	22.42	20.33	16.01
	Im7	**24.83**	24.32	24.76	24.21	17.28	23.53	22.67	**23.58**	21.27	14.92
	Im8	24.69	24.58	**25.54**	23.78	18.95	23.15	23.73	**23.88**	20.47	16.26
	Im9	22.95	24.03	**25.35**	23.79	15.78	22.52	20.86	**22.70**	19.79	16.49

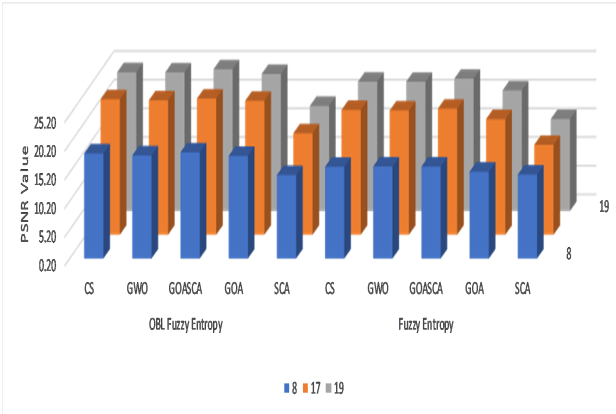
TABLE III: SSIM

K		OFS					Fuzzy Entropy				
		CS	GWO	GOASCA	GOA	SCA	CS	GWO	GOASCA	GOA	SCA
8	Im1	0.6935	**0.7241**	0.7180	0.7172	0.5498	0.6997	0.7044	**0.7146**	0.6805	0.5414
	Im2	0.7802	0.7763	**0.7877**	0.7859	0.6933	0.7504	0.7528	**0.7611**	0.7520	0.6581
	Im3	**0.6838**	0.6187	0.6681	0.5982	0.5654	0.5619	0.5889	**0.6005**	0.5731	0.5547
	Im4	**0.6894**	0.6568	0.6483	0.6728	0.5557	0.5170	**0.5653**	0.5522	0.5366	0.5211
	Im5	0.6436	0.6357	**0.6761**	0.6698	0.4381	0.4439	**0.5342**	0.5114	0.4460	0.4111
	Im6	0.6753	0.6686	**0.6856**	0.6598	0.5984	0.5345	0.5685	**0.5850**	0.5367	0.5721
	Im7	0.7614	0.7467	**0.7750**	0.7346	0.6601	0.6394	**0.7071**	0.6480	0.6364	0.6402
	Im8	0.8305	0.8194	**0.8330**	0.8048	0.7742	0.7867	0.8046	**0.8056**	0.7806	0.7434
17	Im1	0.8654	0.8277	**0.8746**	0.8522	0.6084	0.8365	0.8434	**0.8716**	0.8306	0.5905
	Im2	0.8505	**0.8599**	0.8442	0.8474	0.7293	0.8536	0.8666	**0.8687**	0.8503	0.7206
	Im3	**0.8142**	0.8114	0.8065	0.8005	0.5866	0.7330	0.7722	**0.7736**	0.7264	0.5654
	Im4	0.8339	0.8306	**0.8518**	0.8354	0.6108	0.7513	**0.8275**	0.8101	0.7448	0.6060
	Im5	0.7893	**0.8155**	0.8069	0.7976	0.4938	0.7069	0.7747	**0.7773**	0.6767	0.4797
	Im6	0.7940	0.8024	**0.8061**	0.7981	0.6373	0.7480	**0.8193**	0.7876	0.7288	0.6224
	Im7	**0.8738**	0.8674	0.8689	0.8678	0.6904	0.8019	**0.8635**	0.8414	0.7922	0.6818
	Im8	0.8902	0.8836	**0.8917**	0.8883	0.8434	0.8352	0.8549	**0.8592**	0.8308	0.8118
19	Im1	0.8639	0.8633	**0.8784**	0.8582	0.6072	0.8564	0.8653	**0.8830**	0.8474	0.5989
	Im2	0.8585	0.8755	**0.8976**	0.8577	0.7175	0.8594	0.8741	**0.8762**	0.8577	0.6996
	Im3	**0.8239**	0.8138	0.8149	0.8150	0.5949	0.7410	**0.8019**	0.7928	0.7343	0.5564
	Im4	0.8515	0.8537	**0.8597**	0.8560	0.5810	0.7930	**0.8525**	0.8509	0.7876	0.5769
	Im5	0.8196	0.8079	**0.8413**	0.7914	0.5171	0.7470	0.8093	**0.8361**	0.7149	0.4920
	Im6	0.8276	0.8196	**0.8521**	0.8161	0.6756	0.7698	**0.8400**	0.8339	0.7615	0.6469
	Im7	**0.8898**	0.8818	0.8735	0.8703	0.7675	0.8326	**0.8809**	0.8766	0.8065	0.7275
	Im8	0.8744	0.8887	**0.8996**	0.8827	0.8395	0.8478	0.8703	**0.8711**	0.8372	0.8115

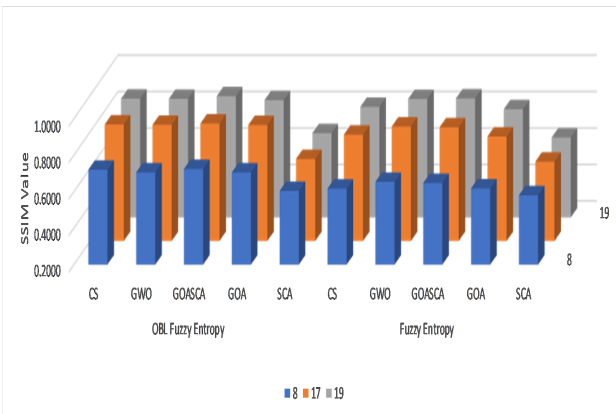
observations. Firstly, the GOASCA based on fuzzy entropy provides results better than the two traditional GOA and SCA overall the tested threshold levels and images except at **Im2** level 8, where the SCA provides better results. This indicates that the combination between the two algorithms is better than using the operators of each algorithm alone. In addition, the performance of the GOASCA outperforms the GWO and CS which achieves the highest PSNR at twelve cases from twenty-four cases. Followed by the CS and GWO which allocates the second and third rank, respectively. Secondly, from the results of PSNR based on the OFS it can be observed that the proposed GOASCA still provides better PSNR values than others at ten images, followed by CS algorithm which has the best PSNR values at seven images. While, the performance of the GWO nearly the same with fuzzy entropy which achieves the highest PSNR value at six images, as well as, GOA provides better PSNR than SCA.

Inspired by the results of SSIM as given in Table III, it can be seen that proposed GOASCA and GWO have the better SSIM value according to use the fuzzy entropy as fitness function. In general, the GOASCA allocates the first rank with fourteen cases from twenty-four, followed by the GWO algorithm with ten cases. While the other algorithms (CS, SCA, and GOA) not achieved the best SSIM value in any case. Moreover, from the results obtained by using the OFS as fitness function, it can be observed that the proposed GOASCA still outperforms the other algorithm which has the highest SSIM value at fifteen cases followed by CS with six cases. Meanwhile, the GWO allocates the third rank with three cases.

Moreover, Fig. 3 depict the average of the methods at each threshold levels and it can see from this Figure the following point. 1) The performance of the five algorithms (i.e., CS, GWO, GOASCA, GOA, and SCA) using OFS at all



(a) PSNR



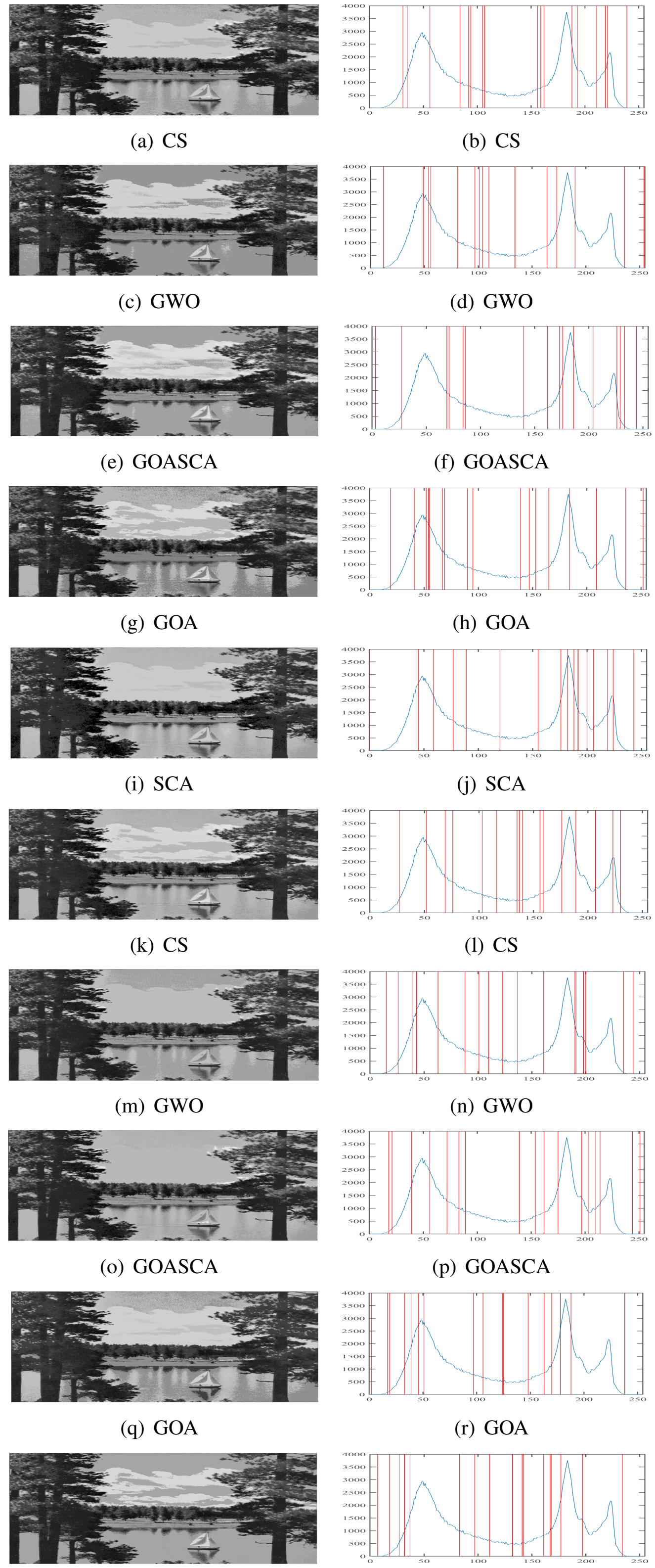
(b) SSIM

Fig. 3: Average of results according to using the two fitness functions in terms of (A) PSNR, (B) SSIM.

the thresholds are better than maximizing the Fuzzy entropy. 2) the proposed GOASCA outperforms the other algorithms among all tested threshold levels. The main reasons for this high quality of the proposed GOASCA are using SCA in competitive manner with GOA to improve the quality of the solutions. In addition, the using difference between the fuzzy entropy and its opposite as fitness function give the MH algorithms high ability to find the near optima solutions in the search space.

Figures 4 depicts the obtained threshold values at level 17 which plotted over the histogram of Im6, in addition to, the segmented images at the same level. From this figure it can be seen the quality of the segmented image based on the threshold obtained from the GOASCA using the two objective functions (i.e., OFS and Fuzzy entropy).

From these results, it can be seen the high quality of the threshold values obtained by the proposed GOASCA over other methods. Moreover, the solutions obtained by OFS are better than using the fuzzy entropy function. This results from combining the opposition of the parameters of fuzzy entropy and its current value during the searching process. However, the proposed GOASCA still have some limitations such as it



(a) CS (b) CS

(c) GWO (d) GWO

(e) GOASCA (f) GOASCA

(g) GOA (h) GOA

(i) SCA (j) SCA

(k) CS (l) CS

(m) GWO (n) GWO

(o) GOASCA (p) GOASCA

(q) GOA (r) GOA

(s) SCA (t) SCA

Fig. 4: Segmented Im6 image and the threshold value over its histograms (Images from (a) to (j) for OFS whereas, images from (k) to (t) for fuzzy entropy).

can stuck at local optima since there are several parameters that need to be defined during the optimization process.

V. Conclusion

This paper proposed provides an alternative multilevel thresholding image segmentation approach using a modified version of the grasshopper Optimization Algorithm (GOA). The proposed approach depends on the sine-cosine algorithm (SCA) to improve the ability of GOA to find the optimal threshold value through allows the GOA and SCA to work in a competitive way. Moreover, the proposed GOASCA aims to minimize the difference between the fuzzy entropy and its opposite value. To evaluate the performance of the proposed GOASCA using these techniques, a set of experiments are conducted using eight images and compared with traditional SCA, GOA, CS, and GWO. The comparison results proved the high quality of segmented images based on the obtained threshold values using the proposed GOASCA in terms of PSNR and SSIM. In addition, the results showed that the objective function based on the difference between the fuzzy entropy and its opposite value outperforms using the fuzzy entropy as a fitness function.

According to the performance of the proposed GOASCA, it can be extended to other applications including feature selection, task scheduling in cloud computing, and other more complex problems in image segmentation. For example, color segmentation, multi-objective image segmentation.

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