Multi-objective Whale Optimization Algorithm for Multilevel Thresholding Segmentation

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Abstract This chapter proposes a new method for determining the multilevel thresholding values for image segmentation. The proposed method considers the multilevel threshold as multi-objective function problem and used the whale optimization algorithm (WOA) to solve this problem. The fitness functions which used are the maximum between class variance criterion (Otsu) and the Kapur's Entropy. The proposed method uses the whale algorithm to optimize threshold, and then uses this thresholding value to split the image. The experimental results showed the better performance of the proposed method to solving the multilevel thresholding problem for image segmentation and provided faster convergence with a relatively lower processing time.

Keywords Multi-objective · Swarms optimization · Whale optimization algorithm · Multilevel thresholding · Image segmentation

1 Introduction

In recent years, the intelligent systems that depend on machine learning and pattern recognition are widely used in numerous fields. These include the application

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of face and voice recognition, objects identification, computer vision, and so on. Nevertheless, the researchers are still working to improve the accuracy of these systems, especially when they are used in real-time environments. When these systems acquire their data from images, they should use image processing techniques to prepare and process the images to be able to identify and recognize the objects on them. Image segmentation is an essential phase in this stage. It works for splitting an image into segments with similar features (i.e., color, contrast, brightness, texture, and gray level) based on a predefined criterion [1]. Image segmentation has been applied in several applications such as medical diagnosis [2], satellite image [3], and optical character recognition [4]. However, it could be a complex process if the images are corrupted by noises from environments or equipment. There are many methods for applying image segmentation, such as edge detection [5], region extraction [6], histogram thresholding, and clustering algorithms [7]; as well as, threshold segmentation [8], it is one of the popular methods for performing this task to locate the best threshold value [9, 10]; it can be divided into two types: bi-level which can be used to produce two groups of objects and multilevel that used to segment complex images and separate pixels into multiple homogeneous classes (regions) based on intensity [1, 11]. Bi-level thresholding method can produce adequate outcomes in cases where the image includes two levels only, however, if it has been used with multilevel the computational time will be often high [12]. On the other hand, the results of bi-level thresholding are not suitable to real application images; so, there is a wide requirement to use multilevel thresholding [11]. There are two methods to determine the thresholds, namely, a global and local level. In a local level, thresholds are determined for each portion of the image; on the other hand, at a global level, one threshold is taken to the whole image [13]. So, by using the image histogram, the global thresholding can be determined. Several thresholding methods explore for the thresholds by optimizing some fitness functions that are defined from images and they handle the determined thresholds as parameters. So, the determination of optimal thresholds in multilevel thresholding is an NP-hard problem [14]. Many methods analyze the image histogram to determine the optimal thresholds, by either minimizing or maximizing a fitness function with consideration of the values of threshold.

When the number of thresholds is small, classical methods are acceptable; but if there are several threshold numbers, it is a best practice to perform a swarm intelligence (SI) technique to optimize this task, such as, genetic algorithm (GA), particle swarm optimization (PSO), firefly optimization (FFO), and bat algorithm.

Jie et al. (2013) [15] introduced a multi-threshold segmentation method that utilized k-means and firefly optimization algorithm (FA). The results showed that the proposed method obtained a low run-time and higher performance than the classical fast FCM and PSO-FFCM models. In the same effort, Chaojie et al. (2013) [16] proposed a method based on FA that outperformed GA algorithm.

Vishwakarma et al. (2014) [17] compared their proposed model that based on FA with the classical K-means clustering algorithm and the model achieved the best results. Sarkar (2011) [18] presented a technique based on differential evolution for multilevel thresholding using minimum cross entropy thresholding (MCET). It was applied to some of the real images and the results showed high efficiency than PSO and GA. Moreover, Fayad et al. [19] proposed a segmentation model based on ACO algorithm. It achieved good results and small errors in comparison to the ground truth. On the other hand, Abd ElAziz et al. [20] introduced a hybrid model that combined SSO and FA (FASSO) for image segmentation. It showed faster convergence and lower preprocessing time. The PSO and its edition [21–26] are implemented in image segmentation to locate the multilevel thresholding. Moreover, there are several swarm techniques that applied for segmentation including honey bee mating optimization (HBMO) [27], harmony search (HS) algorithm [28], cuckoo search (CS) [29], and artificial bee colony (ABC) [30, 31]. However, most of these techniques are either trapped on local optima or predefined control parameters such as GA, PSO, CS, and HS algorithms.

In this chapter, we present a new multilevel thresholding method for image segmentation method. The multilevel thresholding is considered as multi-objective optimization problem, in which the popular two image segmentation functions namely, Otsu's and entropy are used as the fitness function which optimized by the whale optimization algorithm. The properties of these two functions are used to improve the accuracy of image segmentation via multilevel thresholding. The characteristics of the WOA are the ability of fast convergence. The rest of this chapter is organized as follows: Sect. 2 presents the materials and methods. Section 3 introduces the proposed method. Section 4 illustrates the experiments and discussions. The conclusion and future work are given in Sect. 5.

2 Materials and Methods

2.1 Problem Formulation

In this section, the multilevel thresholding problem definition is introduced, by considering an gray level image I contains $K + 1$ groups. Therefore, the $t_k, k = 1, \dots, K$ thresholds are needed to split I to subgroups C_k as in the following equation:

$$\begin{aligned} C_0 &= \{I(i,j) \in I \mid 0 \le I(i,j) \le t_1 - 1\} \\ C_1 &= \{I(i,j) \in I \mid t_1 \le I(i,j) \le t_2 - 1\}, \\ &\dots \\ C_K &= \{I(i,j) \in I \mid t_k \le I(i,j) \le L - 1\}, \end{aligned} \tag{1}$$

where $I(i,j)$ is (i,j)th pixel value and L is the gray levels of $I \in [0, L-1]$.

The aim of the multilevel thresholding is to find the threshold values construct these groups C_k, which can be determined by maximizing the following equation:

$$t_1^*, t_2^*, \dots, t_K^* = \max_{t_1,\dots,t_K} F(t_1, \dots, t_K), \tag{2}$$

where $F(t_1, \dots, t_K)$ may be Kapur's entropy or the Otsu's function.

- Otsu's function:

This function is defined mathematically as

$$F_{Ots} = \sum_{i=0}^{K} A_i(\eta_i - \eta_1)^2, \tag{3}$$

$$A_i = \sum_{j=t_i}^{t_{i+1}-1} P_j, \tag{4}$$

$$\eta_i = \sum_{j=t_i}^{t_{i+1}-1} i\frac{P_j}{A_j}, \quad where \quad P_i = h_i/N, \tag{5}$$

where η_1 is the mean intensity of I with $t_0 = 0$ and $t_{K+1} = L$. The h_i and P_i are the frequency and the probability of the ith gray level, respectively.

- Kapur's Entropy:

The Kapur's entropy function determines the optimal threshold values through maximizing the overall entropy [32] that is defined as:

$$F_{Kap} = \sum_{i=0}^{K}(-\sum_{i=t_i}^{t_{i+1}-1} \frac{P_j}{A_j} ln(\frac{P_j}{A_j})). \tag{6}$$

2.2 Whale Optimization Algorithm (WOA)

The whale optimization algorithm (WOA) is a new meta-heuristic technique that mimics the Humpback whales [33]. In this technique, the optimization begins by producing a random population of whales. These whales search for the prey's (optimum) location, then attach (optimize) them by one of these methods encircling or bubble-net.

In the encircling method [33] the Humpback whales improve their location based on the best location as follows:

$$\mathbf{D} = |\mathbf{C} \odot \mathbf{X}^*(t) - \mathbf{X(t)}| \tag{7}$$

$$\mathbf{X}(t+1) = |\mathbf{X}^*(t) - \mathbf{A} \odot \mathbf{D}|, \tag{8}$$

where $\mathbf{D}$ describes the distance between the position vector of both the prey $\mathbf{X(t)}^*$ and a whale $\mathbf{X(t)}$, and t denotes the current iteration number. $\mathbf{A}$ and $\mathbf{C}$ are coefficient vectors, and defined as follows:

$$\mathbf{A} = 2\mathbf{a} \odot \mathbf{r} - \mathbf{a} \tag{9}$$

$$\mathbf{C} = 2\mathbf{r}, \tag{10}$$

where r is a random vector $\in [0, 1]$, and the value of $\mathbf{a}$ is linearly decreased from 2 to 0 as iterations proceed.

Whereas the bubble-net method can be performed by two approaches. The first is the shrinking encircling that given by reducing the value of $\mathbf{a}$ in equation (9), also, $\mathbf{A}$ is reduced. The last is the spiral updating position. This method is applied to mimic the helix-shaped movement of Humpback whales around prey:

$$\mathbf{X}(t+1) = \mathbf{D'} \odot e^{bl} \odot cos(2\pi l) + \mathbf{X}^*(t), \tag{11}$$

where $\mathbf{D'} = |\mathbf{X}^*(t) - \mathbf{X}(t)|$ is the distance between the whale and prey, b is a constant for determining the shape of the logarithmic spiral, $\odot$ is an element-by-element multiplication, and l is a random value in $[-1, 1]$.

The whales can swim around the victim through a shrinking circle and along a spiral-shaped path concurrently:

$$\mathbf{X}(t+1) = \begin{cases} \mathbf{X}^*(t) - \mathbf{A} \odot \mathbf{D} & if \;\; p \geq 0.5 \\ \mathbf{D'} \odot e^{bl} \odot cos(2\pi l) + \mathbf{X}^*(\mathbf{t}) & if \;\; p < 0.5 \end{cases} \tag{12}$$

where $p \in [0, 1]$ is a random value which describes the probability of choosing either the shrinking encircling method or the spiral model to adjust the position of whales.

In exploration phase, the Humpback whales search randomly for prey. The position of a whale is adjusted by determining a random search agent rather than the best search agent as follows:

$$\mathbf{D} = |\mathbf{C} \odot \mathbf{X}_{rand} - \mathbf{X(t)}| \tag{13}$$

$$\mathbf{X}(t+1) = |\mathbf{X}_{rand} - \mathbf{A} \odot \mathbf{D}|, \tag{14}$$

where $\mathbf{X}_{rand}$ is a random position determined from the current population. Algorithm 1 illustrates the whole structure of the WOA.

3 The Proposed Method

In this section the proposed method for determining the multilevel thresholding values is introduced. In the first the fitness function is defined, based on the combination of the Otsu's and Kapur entropy functions, as

$$Fit = \alpha F_{Ots} + \beta F_{Kap}, \tag{15}$$

where α and β are random values in the range $[0, 1]$ and the parameters represent the balance between the two fitness functions.

The input to the proposed method is the image histogram, the number of whales N and the dimension of each whale position is the threshold level dim. The WOA starting by generating a random population of N solutions in the search domain $[0, L]$ (here $L = 265$), for each position the fitness function Fit_i is computed using equation (15). Then the fitness function F_{best} and its corresponding best whale position x_{best} are determined. Based on each value of decrease the parameter a from 2 to 0, the values of two parameters A and C are computed, then the position of each whale is updated based on the value of the parameter p as illustrated in Sect. 2.2. The previous steps are repeated until the stop criteria are satisfied, and the proposed method is shown in Algorithm 1.

Algorithm 1 Whale Optimization Algorithm (WOA)

Input: dim dimension of each whale, N: number of whales, t_{max}: maximum number of iterations.
Output: x_best Threshold values.
Generate a population of N whales $\mathbf{x}_i$, $i = 1, 2, \ldots, N$
$t = 1$
for all $\mathbf{x}_i$ do // parallel techniques **do**
    Calculate the fitness function Fit_i for $\mathbf{x}_i$.
end for
Determine the best fitness function F_{best} and its position whale x_{best}.
repeat
    for For Each value of a decrease from 2 to 0 **do**
        for $i = 1 : N$ **do**
            Calculate C and A using (10) and (9) respectively.
            $p = rand$
            if $p \geq 0.5$ **then**
                Update the solution using (11)
            else
                if $| A | \geq 0.5$ **then**
                    Update the solution using (14)
                else
                    Update the solution using (7)
                end if
            end if
        end for
    end for
    $t = t + 1$
until $G < t_{max}$

4 Experiments and Discussion

In this section, the experimental environment for the proposed method is introduced. The image description is illustrated in the first, then the setting of the parameters for each algorithm and the measurements used to evaluate the quality of segmentation image is discussed.

Fig. 1 Samples of the tested images, from *left* TestE1, TestE2, TestE3, and TestE7

4.1 Benchmark Images

The proposed methods used in this chapter are tested on four common grayscale images from the database of Berkeley University [34]. These images are called TestE1, TestE2, TestE3, and TestE7 as illustrated in Fig. 1.

4.2 Experimental Settings

The proposed method results are compared with four algorithms, namely, WOA, SSO, FA, and FASSO; these algorithms are previously proposed for multilevel image segmentation and introduced good results. To make the comparison process fair, the population size is 25, the dimension of each agent is the number of thresholds (m) and the same stopping criteria (maximum number of iterations is 100, with a total of 35 runs per algorithm). The parameters of each algorithm used in this paper are illustrated in Table 1.

The experiments were computed on using the following threshold numbers: 2, 3, 4, and 5. All of the methods are programmed in “Matlab 2014” and implemented on “Windows 64bit” environment on a computer having “Intel Core2Duo (1.66 GHz)” processor and 2 GB memory.

Table 1 The parameters setting of each algorithm

Algorithm	Parameters	Value
WOA	a	[0, 2]
	b	1
	l	$[-1, 1]$
SSO	Probabilities of attraction or repulsion (pm)	0.7
	Lower female percent	65
	Upper female percent	90
FASSO	γ_{FA}	0.7
	β_{FA}	1.0
	α_{FA}	0.8
	Probabilities of attraction or repulsion (pm)	0.7
	Lower female percent	65
	Upper female percent	90
FA	γ_{FA}	0.7
	β_{FA}	1.0
	α_{FA}	0.8

4.3 Segmented Image Quality Metrics

The accuracy of the segmented image is evaluated based on fitness function, time, peak signal-to-noise ratio (PSNR), and the structural similarity index (SSIM), where PSNR is defined as

$$PSNR = 20log_{10}(\frac{255}{RMSE}), \quad RMSE = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(I(i,j) - \hat{I}(i,j))^2}{N.M}}, \tag{16}$$

where I and $\hat{I}$ are original and segmented images of size $M \times N$, respectively. The high value of PSNR refers to the high performance of segmentation algorithm. The SSIM is defined as

$$SSIM(I,\hat{I}) = \frac{(2\mu_I\mu_{\hat{I}} + c_1)(2\sigma_{I,\hat{I}} + c_2)}{(\mu_I^2 + \mu_{\hat{I}}^2 + c_1)(\sigma_I^1 + \sigma_{\hat{I}}^2 + c_2)}, \tag{17}$$

where μ_I ($\mu_{\hat{I}}$) and σ_I ($\sigma_{\hat{I}}$) are the mean intensity and the standard deviation of the image I ($\hat{I}$), respectively. The $\sigma_{I,\hat{I}}$ is the covariance of I and $\hat{I}$ and $c_1 = 6.5025$ and $c_2 = 58.52252$ are two constants [35]. The highest value of SSIM and PSNR indicates better performance (Figs. 2, 3, 4 and 5).

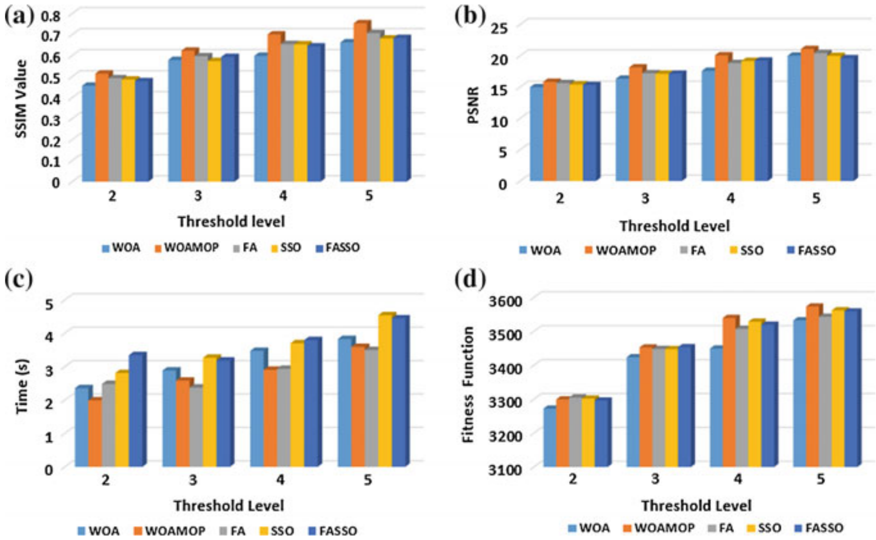

Fig. 2 The average of results of measures overall the testing images

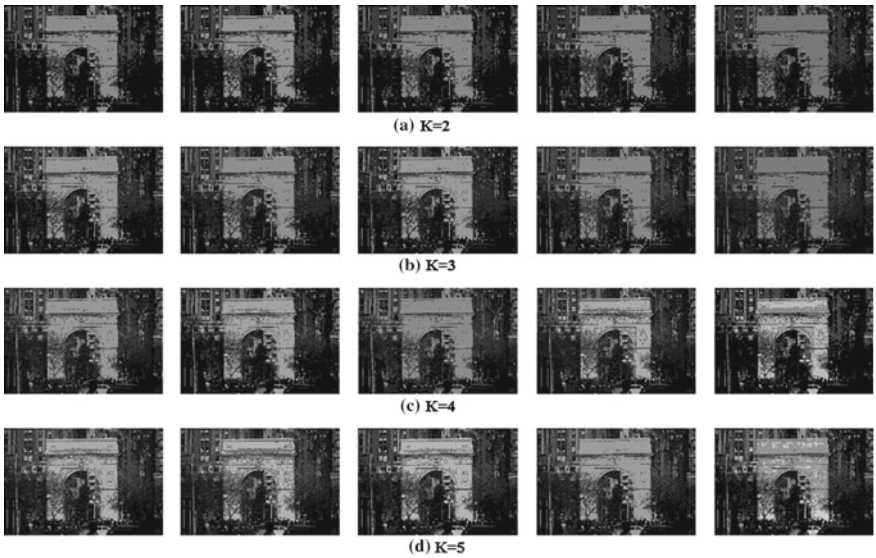

Fig. 3 The result of segmentation TestE1 image using (from *left* to *right*) SSO, FASSO, FA, WOAMOP, and WOA

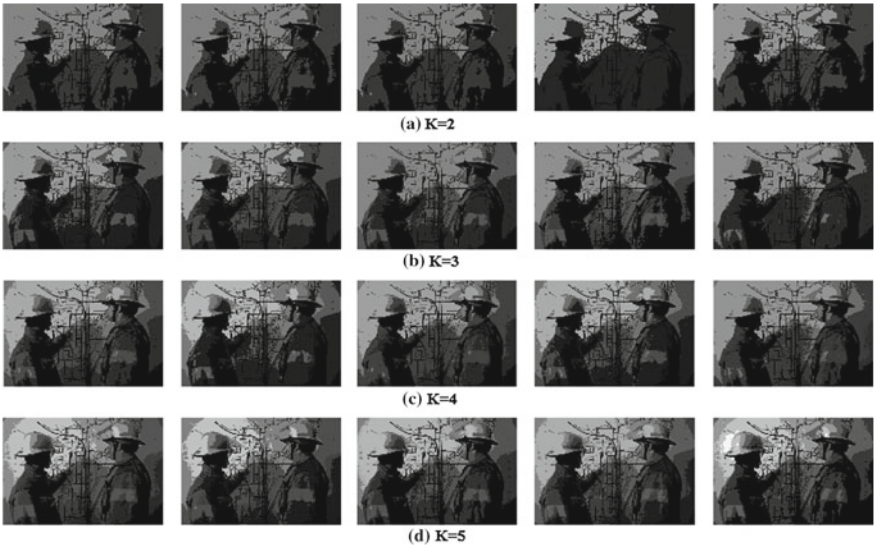

Fig. 4 The result of segmentation TestE2 image using (from *left* to *right*) SSO, FASSO, FA, WOAMOP, and WOA

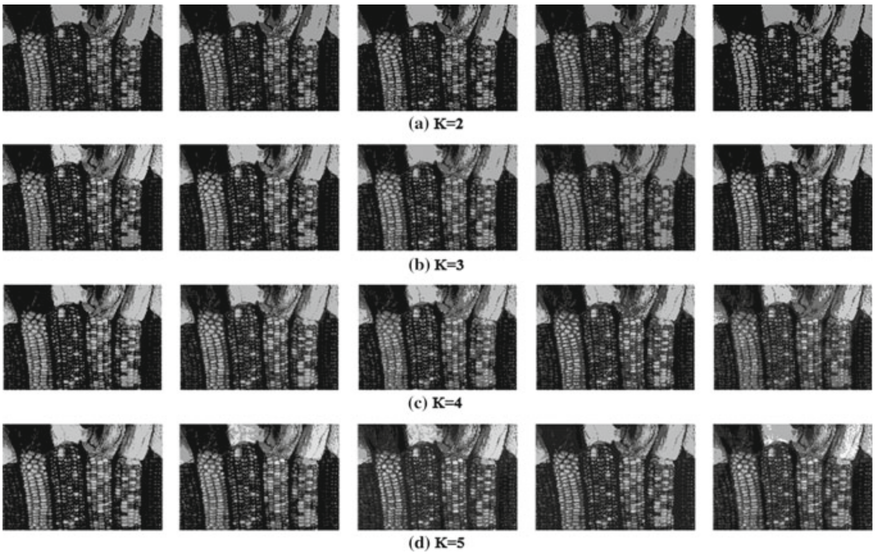

Fig. 5 The result of segmentation TestE3 image using (from *left* to *right*) SSO, FASSO, FA, WOAMOP, and WOA

Table 2 The average of fitness function values and CPU process time of different segmentation techniques

Fitness function							Time (s)				
Images	K	WOA	WOAMOP	FA	SSO	FASSO	WOA	WOAMOP	FA	SSO	FASSO
TestE1	2	3451.335	3473.352	3474.179	3468.534	3460.652	2.3367	2.2682	1.9391	2.5095	2.6167
	3	3556.136	3605.717	3596.408	3615.769	3620.536	2.7800	2.7063	2.3811	3.1488	3.1537
	4	3565.543	3697.336	3673.351	3691.681	3679.444	3.2220	3.1448	3.1551	3.8013	4.1316
	5	3702.948	3744.108	3716.655	3742.238	3730.328	4.0102	3.5838	2.9527	4.0258	4.0410
TestE3	2	3460.841	3535.650	3556.535	3560.862	3550.880	2.3861	1.5464	2.4646	2.5000	4.0586
	3	3711.475	3705.523	3708.666	3695.661	3719.520	2.7932	2.1946	2.5323	3.3532	3.1982
	4	3714.290	3787.483	3757.122	3774.966	3777.062	3.2639	2.1506	2.8329	3.6672	3.7002
	5	3795.133	3832.902	3782.561	3810.940	3821.005	3.7084	3.5551	4.4066	5.3610	5.5121
TestE2	2	4079.675	4100.774	4095.949	4099.082	4081.655	2.3500	2.0995	3.5750	3.6269	3.7653
	3	4243.405	4288.824	4281.223	4273.422	4287.896	3.1398	2.7166	2.2690	3.3195	2.9403
	4	4328.520	4409.415	4370.016	4396.643	4369.280	3.7066	3.1582	2.8544	3.5133	3.5661
	5	4361.881	4443.372	4408.191	4446.256	4411.608	3.7597	3.5995	3.2680	4.2011	4.0670
TestE7	2	2097.983	2088.951	2093.031	2078.644	2090.938	2.3472	2.0487	1.9413	2.6079	2.9397
	3	2185.131	2210.436	2206.062	2205.575	2186.233	2.8317	2.7107	2.3150	3.2536	3.4244
	4	2189.891	2265.325	2229.118	2252.467	2252.220	3.6996	3.1712	2.8970	3.8260	3.7835
	5	2270.616	2273.391	2265.752	2249.944	2272.461	3.8285	3.6192	3.3637	4.5745	4.1576

Table 3 Selected thresholds of techniques

Images	K	WOA	WOAMOP	FA	SSO	FASSO
TestE1	2	63 129	59 141	69 144	77 148	74 155
	3	32 67 133	44 81 144	48 113 161	52 109 159	43 94 151
	4	76 80 146 193	34 73 115 177	39 60 101 148	31 62 105 159	53 101 125 170
	5	54 100 128 157 208	35 67 100 148 165	44 76 133 178 187	31 60 80 129 178	30 58 78 123 184
TestE3	2	115 164	79 167	92 175	88 168	84 169
	3	77 140 192	59 122 159	66 114 182	84 138 209	77 132 189
	4	49 92 123 207	43 103 161 185	91 123 197 82	122 154 200 59	50 112 155 193
	5	47 83 121 184 242	27 72 93 148 195	37 66 110 179 219	72 114 132 178 204	67 95 120 172 225
TestE2	2	72 157	58 144	62 139	62 141	69 139
	3	44 115 150	68 95 151	42 94 142	26 92 161	37 84 164
	4	49 65 117 156	26 83 122 177	41 72 129 167	48 83 125 175	31 97 130 187
	5	63 103 159 198 247	25 67 101 140 179	54 92 137 177 187	42 68 93 149 196	22 72 86 138 199
TestE7	2	55 134	80 151	80 144	71 128	62 130
	3	48 133 176	82 130 175	53 128 159	54 124 155	57 134 180
	4	32 69 132 191	66 108 138 174	69 112 141 190	50 94 141 171	63 99 133 165
	5	37 82 131 149 163	53 92 144 158 170	27 101 121 139 167	53 96 132 173 243	41 107 137 156 197

Table 4 The average PSNR and SSIM of different segmentation techniques

SSIM							PSNR				
Images	K	WOA	WOAMOP	FA	SSO	FASSO	WOA	WOAMOP	FA	SSO	FASSO
TestE1	2	0.4630	0.4997	0.4568	0.4386	0.4445	15.4602	15.7190	15.7193	15.5803	15.6746
	3	0.6428	0.6263	0.5882	0.5819	0.6263	17.1204	18.2775	17.9933	18.0240	18.2690
	4	0.4867	0.7132	0.6846	0.7270	0.6149	16.6475	20.0431	19.1112	19.9239	19.0666
	5	0.6153	0.7250	0.6826	0.7623	0.7579	19.3225	21.0601	20.2145	21.2919	20.8062
TestE3	2	0.3271	0.4083	0.3915	0.4037	0.4092	12.7984	14.1648	13.8011	13.9347	14.0133
	3	0.4888	0.5886	0.5317	0.4583	0.4934	15.4088	16.8358	16.0666	14.9637	15.4732
	4	0.6373	0.6727	0.5579	0.5035	0.6047	17.8221	18.9062	16.6948	15.6900	17.5301
	5	0.6967	0.7857	0.7661	0.5532	0.5773	19.2657	19.7803	20.0627	16.6521	17.0998
TestE2	2	0.4988	0.5558	0.5397	0.5406	0.5084	15.6136	15.4336	15.2995	15.3727	15.1418
	3	0.5950	0.6093	0.6327	0.6055	0.6457	16.4259	17.8354	16.7074	16.9031	17.6821
	4	0.6476	0.6791	0.6729	0.6649	0.6158	18.1127	19.8322	18.9827	19.7417	18.3249
	5	0.5912	0.7168	0.6510	0.6959	0.6675	19.4139	20.8858	20.3041	21.1293	19.4707
TestE7	2	0.5375	0.5947	0.5818	0.5624	0.5512	16.0103	18.0508	17.7184	16.7979	16.4532
	3	0.5896	0.6698	0.6375	0.6495	0.6084	16.4043	19.5508	18.0620	18.6063	17.0253
	4	0.6241	0.7370	0.7040	0.7190	0.7399	17.7795	21.4809	20.5230	21.2755	21.9815
	5	0.7486	0.7876	0.7284	0.7141	0.7313	22.0388	22.5572	21.1294	20.8070	21.0581

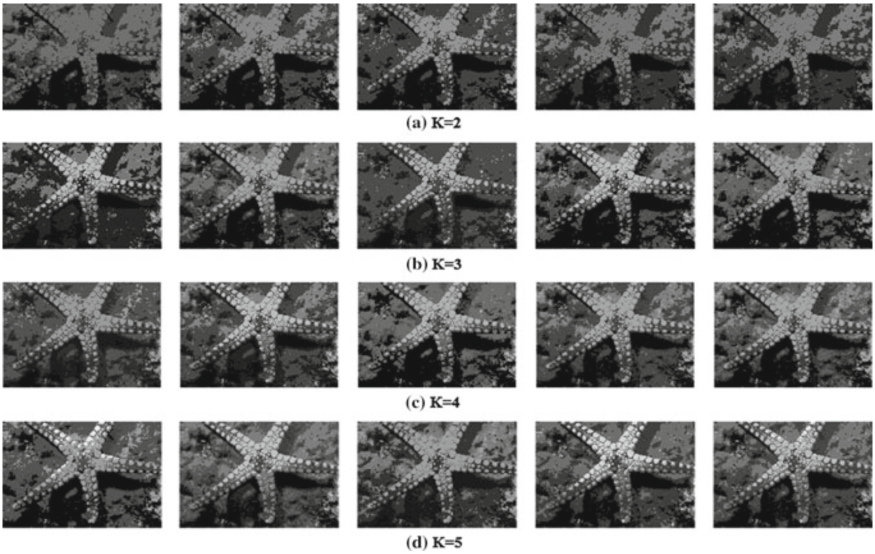

Fig. 6 The result of segmentation TestE7 image using (from *left* to *right*) SSO, FASSO, FA, WOAMOP, and WOA

4.4 The Results and Discussions

The results of comparison between the proposed algorithm and other algorithms are illustrated in Tables 2, 3, 4 and Fig. 6.

In Table 2, the average results of fitness values and time(s) are computed at thresholds 2, 3, and 4. From this table and Fig. 6d we can conclude that, based on the fitness function (as a measure), in general the WOAMOP is the better algorithm than the SSO is in the second rank followed by the FASSO, FA, and WOA. However, at threshold level equal to the FA and SSO give results better than that obtained by WOAMOP, also at level three of segmentation, the FASSO is outperformed WOAMOP (very small difference). At the high-level thresholding (4 and 5) the WOAMOP is better than all other algorithms followed by SSO in the second rank. Also from this table and Fig. 6c the best algorithm based on the time elapsed is the proposed algorithm followed by FA (however, this very small difference).

Table 4 and Fig. 6a–b show the SSIM and PSNR values. From this table and 6b we can observe that, at $K = 2, 3, 4$, and 5 the WOAMOP is better than all other algorithms (however, at $k = 2$ the difference between the algorithm is small). Also, the FA is in the second rank followed by SSO, FASSO, and WOA.

From all previous discussion we can conclude that the proposed method gives better performance based on the quality measures that used (PSNR, SSIM, time, and fitness function).

5 Conclusion and Future Work

Image recognition applications use image processing methods to prepare and process the images to be able to identify and recognize the objects on them. So, image segmentation techniques is an essential preprocessing step in several applications; it divides an image into segments with similar features based on a predefined criterion. In this chapter, a new multi-objective whale optimization algorithm (WOAMOP) was proposed for multi-thresholding image segmentation. The proposed method used the hybrid between the Kapur's entropy and the Otsu's function as a fitness function. The WOAMOP applied to determine the best solution (threshold values) and then used this thresholding values to divide the image. The experiment results of the proposed method were compared with four algorithms, namely, original WOA, FA, SSO, and FASSO. The WOAMOP achieved better results than all algorithms, and also it provides a faster convergence with relatively lower processing time. In future, the WOAMOP can be applied to other complex image segmentation problems such as color images.

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