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Improved Artificial Bee Colony Using Sine-Cosine Algorithm for Multi-Level Thresholding Image Segmentation

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ABSTRACT Multilevel-thresholding is an efficient method used in image segmentation. This paper presents a hybrid meta-heuristic approach for multi-level thresholding image segmentation by integrating both the artificial bee colony (ABC) algorithm and the sine-cosine algorithm (SCA). The proposed algorithm, called ABCSCA, is applied to segment images and it utilizes Otsu's function as the objective function. The proposed ABCSCA uses ABC to optimize the threshold and to reduce the search region. Thereafter, the SCA algorithm uses the output of ABC to determine the global optimal solution, which represents the thresholding values. To evaluate the performance of the proposed ABCSCA, a set of experimental series is performed using nineteen images. In the first experimental series, the proposed ABCSCA is assessed at the low threshold levels and compared with the ABC and SCA as traditional methods. Moreover, the second experimental series aims to evaluate the ABCSCA at high threshold levels and it is compared with six algorithms in addition to the SCA and ABC. Besides, the proposed method is evaluated using the fuzzy entropy. The results demonstrate the effectiveness of the proposed algorithm and showed that it outperforms other algorithms in terms of performance measures, such as Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index (SSIM).

INDEX TERMS Image segmentation, multi-level thresholding, artificial bee colony (ABC), sine-cosine algorithm (SCA).

I. INTRODUCTION

Smart systems using pattern recognition techniques have been applied in several fields in recent years, such as object identification, face recognition, and computer vision. The accuracy of these systems still needs improvement to become more reliable. In addition, the images taken can be corrupted by noise from devices or environments. Image processing techniques have an important role in the preprocessing stage to prepare acquired images to enable object recognition. The basic technique at this stage is called image segmentation. This technique splits an image into different parts according to contrast, color, and brightness [1], [2]. It was applied in various fields such as satellite image segmentation [3], optical character recognition [4], and medical diagnosis [5]. Many approaches have implemented image segmentation, such as region extraction [6], clustering algorithms, histogram thresholding [1], edge detection [7], and threshold segmentation [8]. Threshold segmentation is an efficient approach in the image segmentation tasks. Specifically, it can be applied to find the best threshold value [2]. It is divided into two types: bi-level and multi-level. The first type creates two collections of objects whereas, the second type clusters the pixels into many similar groups [5].

Multi-level thresholding segmentation (MTS) techniques search for optimal thresholds using several methods. The most popular method is by analyzing the histogram of the image [9]. Multi-level thresholding has some challenges such

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as determining the number of thresholds and having a long execution time [10], [11]. When the number of thresholds is small, classical approaches are suitable. However, if there are a large number of thresholds, a good practice is to use a swarm intelligence method to optimize this step. For example, Particle Swarm Optimization (PSO) [12], Genetic Algorithm (GA) [13], Ant Colony Optimization (ACO) [14], Artificial Bee Colony (ABC) [15], and Firefly algorithm (FA) [16]. Although meta-heuristic methods are effective in image segmentation tasks, each method has its shortcomings. Therefore, one effective approach to overcome individual shortcomings is to hybridize these methods together to benefit from their strengths while avoiding their shortcomings. For instance, a hybrid model called FASSO was proposed by [17], it combined the FA and Social Spider Optimization (SSO) algorithm and evaluated them on MTS tasks, the FASSO provided a lower computational time and enhanced the searching phase of the SSO algorithm. Another method was developed by [18] called WOAPSO, it uses the whale optimization algorithm (WOA) and the PSO to separately update the population in parallel; whereas the population is divided into two parts and each part is updated using one of the algorithms then the union of both new solutions is evaluated according to the fitness function. The WOAPSO was tested on MTS; its results outperformed the compared algorithms in terms of the PSNR and the Structural Similarity Index (SSIM) measures.

Moreover, the ABC algorithm was effectively applied on several MTS tasks, it suffers from some drawbacks, such as taking more time to explore the population, requiring many numbers of iterations to reach the optimal solution, and can get stuck in local minima, therefore, in this paper the ABC is improved using the Sine-Cosine Algorithm (SCA) to minimize these drawbacks. The SCA algorithm has many advantages such as low computation requirement and few predefined parameters that provide stable results; it had been applied to solve several problems, for instance [19]–[24].

In general, the SCA and ABC have more attentions in the recent years. They were applied in several types of applications. For example both of them are successfully used for features selection tasks [25], [26], parameter estimation [27], [28], clustering [29], [30], and others. All these applications benefit from the two algorithms due to their advantages in exploring and exploiting the search space.

In this paper, a new segmentation technique based on the hybridization of ABC and SCA is presented. The strengths of these algorithms are utilized to enhance the performance of the MTS phase. The proposed method, called ABCSCA, starts by setting the initial value for a group of N individuals. Each of them represents the threshold values which split the image into its components. The second step computes the objective value of each individual and the best individual is determined which has the best fitness value. The third step updates the individuals using the operators of ABC and SCA in sequential form. In the first, the operators of ABC are used to update the individuals and determine the best solution based on the fitness value of the updated individuals. Secondly, the operators of the SCA are used to update the individuals again which give them high ability to find the optimal solution. The previous two steps are repeated until the stop conditions are met and return the best solution which represents the solution for the multi-level thresholding problem.

The main contribution of this study as follows:

1) Proposed a gray-scale multilevel thresholding image segmentation approach based on hybrid concepts of MH techniques.
2) Combine the strength of the ABC and the SCA to form the proposed ABCSCA method for finding the optimal shareholding value. Evaluate the quality of solutions obtained by ABCSCA through a set of experiments conducted using a set of different images.
3) Evaluate the performance of the ABCSCA with different objective functions namely Otsu's method and fuzzy entropy.
4) Assess the performance of the ABCSCA against other MH methods.

This paper is arranged as follows. Section II presents the literature review. Section III introduces the preliminaries of the problem definition, the ABC, and SCA algorithms. Section IV describes the proposed method. Section V discusses the experimental results. Finally, the conclusion and future work are given in Section VII.

II. LITERATURE REVIEW

In the recent years, metaheuristics have been widely applied in various MTS applications. The PSO algorithm has been applied in the segmentation phase to select MTS [31], [32]. Whereas, the authors of [33] proposed GA for image segmentation and the algorithm achieved competitive results based on Peak Signal-to-Noise Ratio (PSNR) measure. and the Structural Similarity Index (SSIM) measures. In [34], an MTS model based on PSO and BFO is presented. The proposed model had been implemented for both bi-level and multilevel segmentation, and showed good performance with eight images. The FA was proposed in [35] for MTS to improve the performance of the K-means algorithm. The results showed high performance and good segmentation result for the proposed method. On the other hand, the improved FA (IFA) is proposed for MTS by [36] and [37]. The authors of [37] used seven images to test the IFA. The results showed that the IFA effectively selected multi-level thresholds and divided the tested images into background and foreground. In [38], the authors proposed an MTS approach using FA. Otsu method was used as the objective function. Moreover, FA is also applied in several image segmentation applications, such as gray-scale images [39], and RGB color images [40]. The authors of [41] improved the ACO algorithm using Lévy flight pattern then the improved version was used for MTS. The results showed that the improved ACO obtained the optimal thresholds faster than the traditional Otsu's method. Satapathy *et al.* [42] proposed an

MTS method based on chaotic bat algorithm (CBA) and the Otsu method was used as the objective function. The proposed method showed better performance than several state-of-arts methods such as PSO, FA, and bacterial foraging optimization (BFO). Varsha *et al.* [43]presented a new MTS method based on chaotic cuckoo search (CCS) and Tsallis entropy. Moreover, Cuckoo Search algorithm has been successfully applied for both gary-scale images [44] and color images [44], [45] and it assesses its quality. The ABC was tested in MTS task by [46]; they decomposed images by discrete wavelet transform and applied noise reduction. The results outperformed the GA and the Artificial Fish Swarm algorithm in terms of accuracy and execution time. Rajinikanth and Satapathy [47] applied social group optimization (SGO), Fuzzy-Tsallis entropy and Ischemic Stroke Lesion (LSI) for magnetic resonance image (MRI) image segmentation. In [48], the SGO also applied with Kapur and Otsu for melanoma images and achieved promising results.Another MRI segmentation method was proposed by [49], by using teaching learning based optimization (TLBO). Also, Rajinikanth *et al.* [50] proposed active contour snake model with Otsu's multi-thresholding to detect cancerous regions in tested images.

Mousavirad and Ebrahimpour-Kom [51]proposed an MTS method by using human mental search algorithm. They used both Otsu and Kapur as fitness functions. The proposed method had been evaluated with twelve images. In [52], [53], the authors compared several metaheuristics for MTS using Kapur's entropy. Bhandari [54] proposed an MTS approach based on beta differential evolution (BDE) and both Kapur and Tsallis entropy are used as fitness functions. The BDE based approach had been compared with several metaheuristics and it showed better performance. Monisha *et al.* [55] used Shannon function and social group optimization (SGO) for RGB MTS. The proposed SGO method outperforms several MTS methods, including FA, BFO, PSO, and BA. Furthermore, Jia *et al.* [56] applied an improved grasshopper optimization algorithm (GOA) for MTS method for Satellite images. The self-adaptive differential evolution is merged with GOA to improve the search process. The proposed method showed good performance in different evaluation tests. Bao *et al.* [57] applied a hybrid method based on Harris hawks optimization and differential evolution method for MTS. Both Otsu's and Kapur's entropy were used as fitness function. The proposed method had been evaluated with color images and it showed promising performance. The ABC was also used for MTS by [58] and applied to segment iris images. The numerical results of ABC outperformed the compared methods. Moreover, ABC was improved and applied by [59]. It was evaluated using six benchmark images and three thresholds levels. The experiments result recorded that the improved ABC showed better-segmented images than the compared algorithms. In this context, the authors of [60] improved the searching phase of the ABC, then, it was evaluated using eight gray images and three thresholds levels (i.e. 2, 3, and 4). The results were compared with Otsu's method and the state-of-the-art algorithms, they showed good performance in terms of the fitness value and consuming time.

III. PRELIMINARIES

A. OTSU's THRESHOLDING

In this section, the mathematical definition of multi-level thresholding problem is introduced. Let I represents a gray image that contains $K+1$ classes. Therefore, to split the image into subclass C_K ($k = 1, \ldots, K+1$), it is necessary to determine K thresholds $\{t_1, t_2, \ldots, t_K\}$ as $C_0 = \{I(i,j) \in I \mid 0 \le I(i,j) \le t_1 - 1\}$, $C_1 = \{I(i,j) \in I \mid t_1 \le I(i,j) \le t_2 - 1\}$ and, $C_K = \{I(i,j) \in I \mid t_K \le I(i,j) \le L-1\}$.

Here, $I(i,j)$ and L represent the gray level of the pixel (i,j) and the number of distinct gray levels within I, respectively.

The aim of the multi-level thresholding method is to determine the best threshold values, which are located by maximizing Equation (1) known as Otsu's function [61]:

$$t_1^*, t_2^*, \ldots, t_K^* = \max_{t_1,\ldots,t_K} F(t_1, \ldots, t_K) \tag{1}$$

$$F = \sum_{i=0}^{K} A_i(\eta_i - \eta_1)^2, \quad A_i = \sum_{j=t_i}^{t_{i+1}-1} P_j, \tag{2}$$

$$\eta_i = \sum_{j=t_i}^{t_{i+1}-1} i\frac{P_j}{A_j}, \quad where \quad P_i = h(i)/N, \tag{3}$$

where P_i and $h(i)$ represent the probability and the frequency of the ith gray level, respectively, and, η_1 represents the mean intensity of I (note that $t_0 = 0$ and $t_{K+1} = L$).

The Otsu's function is used in this paper as a fitness function. Otsu's method is generally widespread in the field of segmentation and thresholding. It is used to perform automatic histogram shape-based image thresholding. It works to determine the best threshold in images that contain two classes of pixels (e.g. background and objects) to separate these classes and minimize the intra-class variance thus, it can effectively divide the background from the objects besides, it has applied by many recent studies [62]–[64].

B. ARTIFICIAL BEE COLONY (ABC)

Artificial Bee Colony (ABC) is an optimization algorithm inspired by the behavior of real honey bees' colony [65]. It consists of three collections. The first one is employed bees. This collection searches for new food sources and the information about this phase is transferred to the second collection (onlooker bees). The onlooker bees use this information to choose a food source. The third collection (scout bees) searches randomly for a food source. The ABC algorithm generates a random population of N solutions that describes the employed bee $x_i \in R^d$, $i = 1, 2, \ldots, N$. The new solution v_i is generated based on x_i as follows [66]:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}), \quad k = int(rand * N), \; j = 1, \ldots, d \tag{4}$$

where x_k is a neighbor employed bee of x_i, $\phi_{ij} \in [-1, 1]$ and it is created in a random manner.

The objective functions for Fx_i and Fv_i are computed for x_i and v_i respectively; then, if $Fx_i \leq Fv_i$, the solution x_i is removed from the memory of the first collection and v_i is added. The objective function Fx_i which is obtained from employed bees is transferred to the onlooker bees. Thereafter, the roulette wheel selection method is used to determine the x_i that has a higher probability of having the objective function (P_i), which is calculated as:

$$P_i = \frac{fit_i}{\sum_{i=1}^{N} fit_i}, \quad fit_i = \begin{cases} \dfrac{1}{1+Fx_i} & \text{if } Fx_i > 0 \\ 1 + abs(Fx_i) & \text{otherwise} \end{cases} \tag{5}$$

Each one of the onlooker bees updates its solution via the same process used by the employed bees. The onlooker bee tests both the new and old solutions to decide whether the old solution is removed from the memory or not. If there is no difference in the solutions after a particular number of repetitions, these solutions are discarded; then the scout bee group explores a new solution to update x_i as:

$$x_{ij} = x_j^{min} + (x_j^{max} - x_j^{min}) \times \delta \tag{6}$$

where x_{ij} is an optimized parameter for the ith employed bee, x_j^{min} and x_j^{max} are the lower and upper bounds for x_{ij} respectively, and δ is a random number. After a new solution x_{ij} is generated, it becomes an employed bee.

C. SINE-COSINE ALGORITHM (SCA)

The Sine-Cosine Algorithm (SCA) is a meta-heuristic algorithm. It utilizes the mathematical forms of sine and cosine for application to optimization issues [67]. SCA starts the optimization process by producing various random solutions, then initializes iterations to achieve the best solution. The best solution is defined as the target point. While continuing the iteration process, the sine and cosine ranges are adjusted based on their mathematical forms to better exploit the search space. The iterations are stopped if the stop condition is satisfied. The following equation determines the mathematical form of SCA:

$$A_k^{t+1} = \begin{cases} A_k^t + n_1 \times sin(n_2) \times |n_3 P_k^t - A_k^t|, & n_4 < 0.5 \\ A_k^t + n_1 \times cos(n_2) \times |n_3 P_k^t - A_{kk}^t|, & n_4 \geqslant 0.5 \end{cases} \tag{7}$$

where A_k^{t+1} is the position of the current solution in the kth dimension, t determines the current iteration, n_1, n_2, and n_3 are random numbers, P_k is the position of the target point in the kth dimension, n_4 is a random number in [0, 1].

The range of sine and cosine in Equation (7) by decreasing the value of n_1 (i.e. $n_1 = c - t \times c/T$, where T is the length of iterations, and c is a constant).

D. PERFORMANCE MEASURES

Four popular measures are used in this paper to evaluate the performance of the proposed algorithm for image segmentation. The first two measures are the fitness function as in Equation (1) and CPU time. The third measure is the Peak Signal-to-Noise Ratio (PSNR) [68] [69] as in Equation (8). The fourth measure is the Structural Similarity Index (SSIM) [70] as in Equation (10).

$$PSNR = 20log_{10}(\frac{255}{RMSE}) \tag{8}$$

where the root mean-squared error ($RMSE$) is represented as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{Q}(Org(i,j) - Seg(i,j))^2}{M \times Q}} \tag{9}$$

where Org is the original image and the segmented image is Seg of size $M \times Q$.

$$SSIM(Org, Seg) = \frac{(2\mu_I \mu_{Seg} + c_1)(2\sigma_{Org,Seg} + c_2)}{(\mu_I^2 + \mu_{Seg}^2 + c_1)(\sigma_{Org}^2 + \sigma_{Seg}^2 + c_2)} \tag{10}$$

where μ_{Org} and μ_{Seg} are the images' mean intensity (Org and Seg); σ_{Org} and σ_{Seg} indicate the standard deviation of both images; $\sigma_{Org,Seg}$ represents the covariance of the images Org and Seg; $c_1 = 6.5025$ and $c_2 = 58.52252$ are constants.

IV. PROPOSED ABCSCA ALGORITHM

In this section, we introduce a hybrid algorithm to segment images via determining the optimal multi-level thresholding values that maximize Otsu's objective function. The proposed algorithm is called ABCSCA and is based on the ABC and SCA algorithms. ABCSCA uses Otsu's function as an objective function.

The ABC is used to reduce the search region by determining the best solution; SCA then searches in that reduced region. Therefore, the ABCSCA algorithm starts by computing the histogram of an input image and then generates a random population of N solutions (representing the threshold values). Then, the ABC updates this population using its three groups of bees as discussed in Section III-B. Thereafter, the best solution is determined from the population based on maximizing Equation (1) (the best solutions from the ABC algorithm).

The SCA begins determining the optimal thresholding value by using the output from the ABC (best solution) and updating the solutions of the population via the strategy discussed in Section III-C. The global optimal solution (the output of the SCA algorithm) is determined, and all the previous steps are repeated until the stopping conditions are met. The final steps of the ABCSCA is illustrated in Figure 1.

V. EXPERIMENTS AND RESULTS

In this section, we performed a set of experimental series to evaluate the performance of the proposed ABCSCA algorithm.

A. EXPERIMENTAL SERIES 1: LOW THRESHOLD LEVELS

In this section, we will evaluate the performance of the proposed method at the low threshold levels (i.e., 2, 3, 4, and 5). In addition, we compared it with three other algorithms,

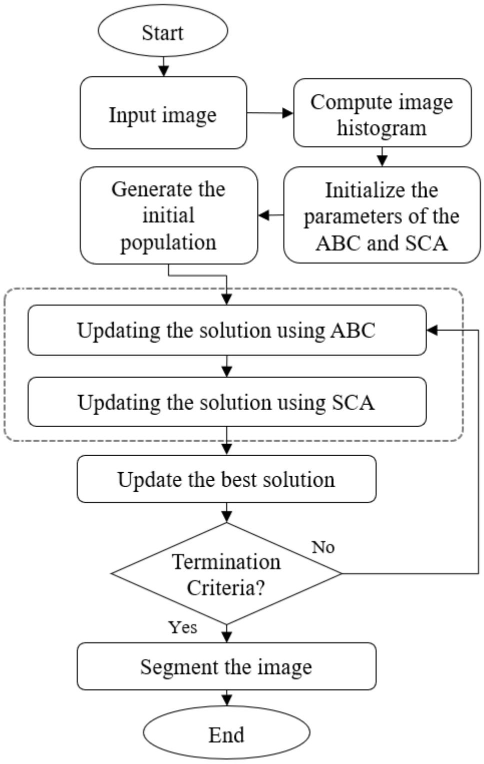

FIGURE 1. **The workflow of the ABCSCA.**

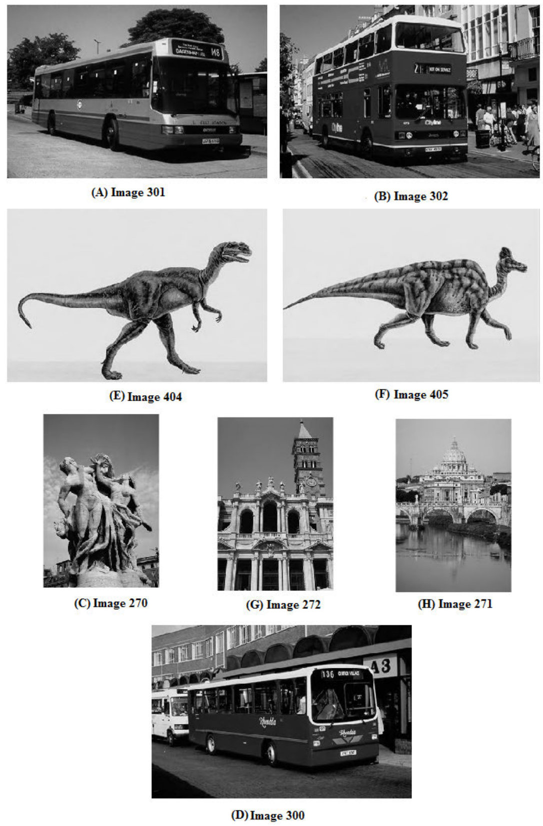

FIGURE 2. **The Original eight images that used in the experiments [71], [72].**

namely ABC [66], SCA [67], and FASSO [17]. These three have been applied previously and provided good performance in terms of SSIM and PSNR. In the comparison process, the size of the population (number of solutions) is set to 20, with the dimension equals to the threshold level. The maximum number of iterations is set to 100, which is used as stopping criteria, these parameters are selected experimentally and due to the recommendation in the previous works [2], [8], [63].

The experiments were performed based on four thresholding levels 2, 3, 4, and 5. The parameter of ABC is a modification rate of 0.8. For FASSO, the parameters are the same as in [17]. For SCA, the parameter a is set to 2 and the parameters of ABCSCA are the same as for ABC and SCA. Figure 2 shows the eight images (from the Art Explosion database) which were used to test algorithms; these images are, namely, image 270, image 271, image 272, image 300, image 301, image 302, image 404 and image 405.

The comparison results of the proposed ABCSCA algorithm with the other three algorithms are given in Tables 1-3 and Figures 3-6. The results represent the average of 30 runs of each algorithm at each threshold level. Whereas, Figures 7-8 illustrate a sample of the segmentation results.

Table 1 represents the average of the fitness function and the time(s) of computation for all algorithms at thresholding levels 2, 3, 4 and 5 for overall images. According to Figure 3 and Table 1, we can see that, the SCA algorithm takes the longest time, and that the ABC algorithm needs more time than the FASSO and ABCSCA algorithms. The proposed ABCSCA algorithm also needs less time to deal with low threshold levels problem (at levels 2 and 3). However, FASSO is better than ABCSCA at threshold levels 4 and 5.

From Figure 4 and Table 1, in terms of the average of the fitness function, the proposed ABCSCA algorithm is the best for threshold levels 4 and 5, but at level 3, FASSO is better than ABCSCA. Additionally, at threshold level 2, the least accurate is the ABCSCA algorithm.

Table 2 and Figures 5-6 show the results of the algorithms according to the SSIM and PSNR measures. From this table and Figure 5, we can conclude that the proposed algorithm is better at the higher levels of thresholding and less accurate (based on SSIM measure) at low levels. However, at these low levels, the difference is small.

Moreover, in terms of the PSNR measure (as in Figure 6), the average of ABCSCA is better than all other algorithms among the threshold levels. The FASSO algorithm ranks second, followed by the ABC algorithm, and the least accurate algorithm is the SCA algorithm.

Drawing from all of these results, that can be concluded, the proposed ABCSCA algorithm overcomes the drawbacks of the SCA and ABC algorithms. Moreover, ABCSCA gives better values of SSIM and PSNR for image segmentation than the ABC and SCA algorithms. In addition, ABCSCA generally gives better segmentation results than FASSO based

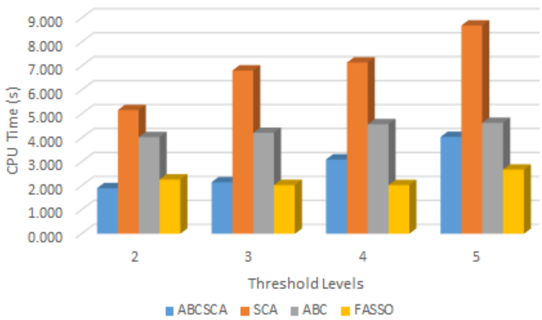

FIGURE 3. The average of the CPU time(s) values overall images.

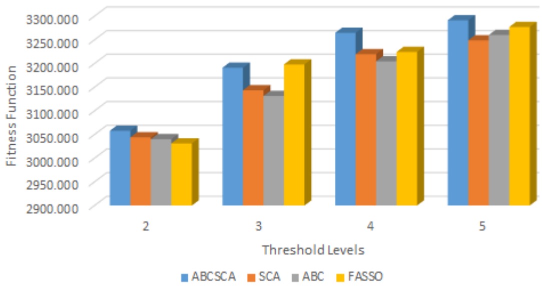

FIGURE 4. The average of the fitness function values overall images.

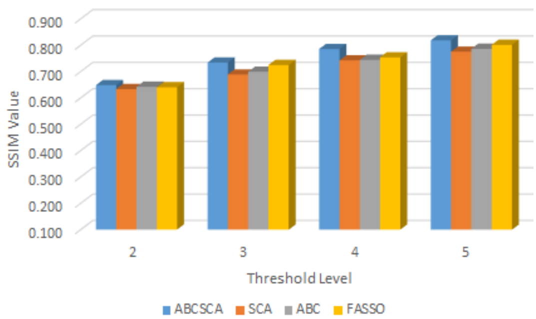

FIGURE 5. The average of the SSIM measures values overall images.

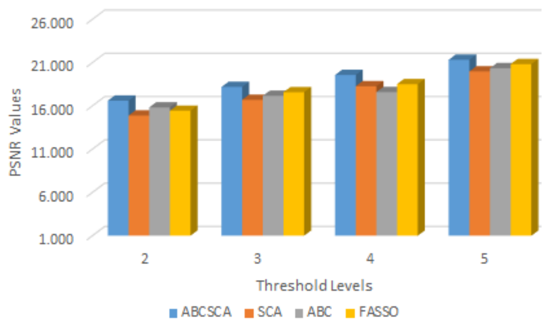

FIGURE 6. The average of the PSNR measures values overall images.

FIGURE 7. Results of image 272 at levels 2,3, 4, and 5 (from first row to fourth row, respectively).

on the SSIM and PSNR measures. In terms of CPU time(s), the ABCSCA is significantly improved the slow processing times of the ABC and SCA algorithms in selecting the optimal threshold's values by 64% and 36%, respectively. The ABCSCA prevents the long searching time for optimal thresholds that taken by the two algorithms. As well as, the ABCSCA outperformed the FASSO at threshold level 2 whereas, the FASSO is faster than ABCSCA at the rest levels however, the CPU time of the ABCSCA is still acceptable.

In addition, the standard deviation of the results overall the threshold values are given in the last row of Tables 1-2, illustrate that the proposed ABCSCA is more stable than other algorithms in terms fitness value, and PSNR. Meanwhile, ABC in terms of SSIM and CPU time(s).

The non-parametric statistical test called Wilcoxon's rank sum (WRS) is used to further investigate the accuracy of the proposed ABCSCA algorithm for image segmentation. The WRS test compares the median of two groups (methods), which produces a statistical value ($p - value$) to decide whether to accept or reject the null hypothesis ($H0$). Where, the null hypothesis $H0$ assumes that there is no significant difference between the two groups (i.e., the median values for the two groups are the same). This hypothesis is accepted if the $p - value$ is greater than 0.05, otherwise, the null hypothesis $H0$ is rejected and the alternative hypothesis ($H1$) is accepted.

The results of the WRS test according to four measures (PSNR, SSIM, Fitness function and CPU Time(s)) are given in Table 3. From this table, according to the PSNR and time measures, there is a significant difference between the proposed ABCSCA algorithm and the SCA and ABC algorithms (p-value<0.05). There is, however, no significant difference between ABCSCA and FASSO (p-value>0.05). Moreover, based on the fitness function and the SSIM, there is no significant difference between the proposed method and the other methods.

TABLE 1. Average of the fitness function values and CPU times for all algorithm.

		Fitness Function				CPU Time (s)			
Images	K	ABCSCA	SCA	ABC	FASSO	ABCSCA	SCA	ABC	FASSO
270	2	2790.06	2640.08	2680.93	2733.85	2.16	3.43	4.27	1.85
	3	2852.89	2705.89	2735.68	2790.99	2.60	3.42	3.80	2.90
	4	2940.19	2889.39	2862.53	2906.26	4.33	4.09	4.05	2.08
	5	2948.13	2903.31	2896.70	2937.93	8.17	4.55	3.93	3.20
271	2	2258.63	2111.86	2102.10	2109.04	3.37	5.95	3.70	2.76
	3	2418.47	2295.68	2209.98	2403.53	2.26	7.39	3.94	1.92
	4	2463.17	2359.60	2345.64	2426.57	3.65	9.36	4.92	2.26
	5	2494.19	2415.93	2423.69	2442.92	5.29	10.81	4.34	3.27
272	2	2983.00	3000.81	3022.61	2942.95	1.31	5.65	3.81	1.09
	3	3185.96	3136.42	3147.86	3118.41	1.18	7.13	3.90	1.23
	4	3207.28	3160.46	3165.77	3125.12	3.12	7.93	4.25	1.08
	5	3211.55	3206.08	3230.91	3215.54	3.60	12.76	5.78	3.52
300	2	3123.40	3094.38	3077.27	3050.61	1.83	7.62	4.95	3.00
	3	3198.46	3148.53	3121.73	3314.14	3.00	9.56	5.38	1.18
	4	3358.22	3224.91	3239.79	3312.90	3.40	7.67	5.63	2.06
	5	3340.40	3285.22	3302.55	3324.36	3.59	9.67	4.74	2.43
301	2	3545.38	3616.29	3600.62	3581.55	1.37	4.17	3.78	1.01
	3	3648.67	3644.84	3630.44	3739.15	1.85	7.28	4.19	2.95
	4	3744.04	3771.60	3759.08	3734.38	2.00	7.28	4.83	2.38
	5	3835.91	3732.08	3783.63	3817.44	2.62	8.28	4.77	2.06
302	2	3419.85	3539.09	3488.76	3491.87	1.40	4.09	4.04	2.78
	3	3756.70	3716.33	3791.53	3793.10	1.95	6.52	4.07	2.05
	4	3886.02	3878.35	3784.99	3827.51	2.74	7.64	4.28	2.09
	5	3944.13	3934.45	3933.95	3961.71	3.28	7.21	4.61	2.30
404	2	3368.66	3383.93	3368.84	3368.26	1.85	5.71	3.84	2.81
	3	3388.63	3400.76	3373.84	3411.56	1.97	6.55	4.24	1.09
	4	3427.58	3430.69	3426.89	3417.42	2.75	6.32	4.39	2.20
	5	3490.79	3453.70	3450.52	3456.67	2.86	8.20	4.22	2.25
405	2	2975.23	2966.11	2978.92	2971.02	1.91	4.67	3.88	2.82
	3	3078.53	3099.49	3040.83	3013.13	2.37	6.65	4.17	2.97
	4	3092.17	3042.60	3051.94	3044.78	2.84	6.87	4.23	2.09
	5	3065.04	3060.21	3058.88	3059.54	2.92	8.06	4.62	2.40
STD.		430.8512	466.7548	469.2860	457.8820	1.3422	2.1336	0.5353	0.6968

TABLE 2. Average of SSIM and PSNR values for all algorithm.

		SSIM				PSNR			
Images	K	ABCSCA	SCA	ABC	FASSO	ABCSCA	SCA	ABC	FASSO
270	2	0.722	0.555	0.580	0.695	17.11	12.97	15.00	16.33
	3	0.760	0.656	0.693	0.712	17.76	15.69	16.28	16.92
	4	0.781	0.730	0.747	0.756	19.32	18.07	17.61	18.32
	5	0.807	0.764	0.755	0.793	21.48	19.94	19.40	20.75
271	2	0.743	0.681	0.683	0.713	15.56	15.46	15.82	15.46
	3	0.800	0.706	0.725	0.786	18.95	17.99	17.72	17.18
	4	0.827	0.752	0.781	0.813	19.90	18.62	17.11	19.40
	5	0.834	0.785	0.807	0.828	20.72	19.31	19.28	19.85
272	2	0.635	0.642	0.699	0.614	15.10	14.17	15.58	13.50
	3	0.803	0.716	0.722	0.790	19.40	17.11	16.70	19.07
	4	0.838	0.761	0.770	0.802	20.07	18.08	19.87	20.04
	5	0.849	0.781	0.792	0.827	20.56	19.43	20.20	20.74
300	2	0.445	0.458	0.468	0.402	16.51	16.54	16.30	16.40
	3	0.595	0.521	0.480	0.562	18.21	17.77	17.87	18.88
	4	0.647	0.592	0.594	0.619	19.77	18.70	19.61	19.34
	5	0.710	0.631	0.672	0.764	20.81	18.83	20.74	19.62
301	2	0.419	0.548	0.531	0.552	18.89	15.52	17.89	17.87
	3	0.438	0.559	0.547	0.506	18.66	17.76	17.98	19.72
	4	0.591	0.571	0.591	0.595	21.96	19.90	20.11	18.84
	5	0.670	0.607	0.689	0.636	22.10	18.13	21.76	22.74
302	2	0.449	0.442	0.432	0.417	15.01	15.58	15.20	15.30
	3	0.654	0.581	0.653	0.630	18.08	15.84	18.21	17.97
	4	0.752	0.722	0.678	0.630	19.45	19.67	18.25	19.27
	5	0.783	0.763	0.743	0.724	20.74	20.83	21.47	20.12
404	2	0.876	0.873	0.860	0.843	18.89	13.38	14.83	11.27
	3	0.892	0.891	0.846	0.890	16.64	17.53	13.68	14.20
	4	0.913	0.905	0.885	0.891	17.21	18.59	13.07	13.88
	5	0.929	0.926	0.898	0.904	22.65	23.74	21.05	20.80
405	2	0.897	0.865	0.883	0.886	15.74	15.43	15.96	17.35
	3	0.929	0.880	0.926	0.921	17.81	13.89	18.85	16.66
	4	0.934	0.906	0.910	0.923	18.87	14.53	15.16	19.03
	5	0.964	0.942	0.935	0.935	21.50	19.57	18.99	21.99
STD.		0.1556	0.1425	0.1392	0.1469	2.0893	2.3986	2.2918	2.5903

B. EXPERIMENTAL SERIES 2: INFLUENCE OF HIGH THRESHOLDS

The main aim of this experiment is to evaluate the quality of the proposed ABCSCA to find suitable threshold values to segment a set of different eleven images (as in Figure 9) at high-level thresholds (i.e. 6, 12, 16, and 20). These images are used to check the ability of the proposed ABCSCA to work a large number of images. In addition, the performance of the proposed ABCSCA is compared with a set of recently published methods. These methods including, salp swarm algorithm (SSA), whale optimization algorithm (WOA), grey wolf optimization (GWO), and social spider optimization (SSO) as well as the methods used in the previous experiments. The values of parameters of each algorithm are set

FIGURE 8. Results of image 271 at levels 2,3, 4, and 5 (from first row to fourth row, respectively).

TABLE 3. Statistical results of Wilcoxon's rank sum test at significance level equals to 0.5 between ABCSCA and the other algorithms over all measures.

		SCA	ABC	FASSO
PSNR	$p-value$	0.0088	0.0291	0.2797
	h	1	1	0
SSIM	$p-value$	0.2167	0.3270	0.5236
	h	0	0	0
Fitness function	$p-value$	0.8038	0.7728	0.7935
	h	0	0	0
CPU Time	$p-value$	0.0000	0.0000	0.1361
	h	1	1	0

as on the original reference. Those methods are used since they established their performance as image segmentation methods in the literature.

The comparison results are given in Tables 5-4 and Figures 10-11. Table 5 and Figure 10 present the PSNR results of the ABCSCA and the compared methods. The ABCSCA outperformed all other methods and ranked first, it reached the best PSNR results in 41% of all images overall thresholds. The SCA came in the second rank with 14% of all images overall thresholds whereas, it showed the best PSNR in the thresholds numbers 12 and 16. The FASSO obtained 11% of the best PSNR in this experiment. The WOA and SSA are ranked fourth and fifth, respectively, with 9% for each one, followed by the SSO. The ABC came in the seventh rank and it showed the best PSNR in the thresholds numbers 6 and 20. Whereas, WOAPSO and GWO are ranked last.

The results of SSIM are also considered as in Table 4 and Figure 11. From this table, it can be seen that the ABCSCA achieved the best SSIM results in 39% of all test images

FIGURE 9. The Original eleven images that used to assess proposed method at the high threshold levels.

TABLE 4. Average of the PSNR values for all algorithm for 6, 12, 16, and 20 thresholds.

		SSA	WOA	GWO	SSO	SCA	ABC	FASSO	WOAPSO	ABCSCA
6	Im1	20.46	20.27	20.83	20.66	20.25	20.65	20.45	20.69	**20.83**
	Im2	18.28	18.51	18.38	18.76	18.37	18.31	18.48	18.17	**19.93**
	Im3	19.65	19.65	19.40	19.96	19.49	19.01	19.40	19.52	**20.21**
	Im4	21.16	21.08	21.07	21.17	21.15	20.89	21.31	21.10	**21.47**
	Im5	20.10	19.46	18.99	19.31	19.70	19.07	18.59	19.77	**20.94**
	Im6	19.48	19.79	19.38	19.40	19.78	19.06	19.46	19.33	**20.46**
	Im7	**19.95**	19.54	19.59	19.57	19.14	19.48	19.26	19.39	19.30
	Im8	**19.95**	19.80	19.47	19.03	19.56	19.72	19.38	19.66	19.48
	Im9	16.98	17.73	17.71	17.24	17.96	17.69	17.63	17.78	**19.13**
	Im10	18.75	18.29	17.64	18.64	18.26	18.01	17.93	18.74	**18.80**
	Im11	18.16	17.51	17.92	**18.49**	17.66	17.91	17.81	17.66	18.07
12	Im1	24.33	24.53	24.83	24.54	24.30	**24.95**	24.49	24.54	24.94
	Im2	23.13	22.87	23.18	22.07	22.50	23.17	22.73	22.35	**23.52**
	Im3	**24.76**	24.43	24.27	24.51	24.56	24.64	24.70	24.57	24.53
	Im4	25.57	25.59	25.45	25.51	25.58	25.56	**25.72**	25.11	25.24
	Im5	24.41	24.42	24.05	24.61	**25.10**	24.54	24.54	24.32	24.81
	Im6	24.62	24.49	24.63	24.13	24.47	24.61	**24.66**	24.34	24.63
	Im7	**24.62**	24.28	24.19	24.58	23.91	24.43	24.25	24.21	24.54
	Im8	23.75	24.06	23.68	24.31	24.23	**24.45**	23.98	24.19	24.20
	Im9	22.52	22.96	22.45	22.37	22.30	22.16	22.51	23.01	**23.73**
	Im10	22.75	**23.16**	21.99	22.04	23.04	21.70	22.81	22.65	22.93
	Im11	23.10	22.65	23.23	**23.46**	22.57	23.28	22.93	23.31	23.37
14	Im1	26.36	26.52	26.28	**26.71**	25.40	25.72	25.18	25.79	26.56
	Im2	24.06	**24.98**	24.46	24.50	24.07	24.28	23.47	24.12	24.95
	Im3	26.43	26.84	26.54	26.54	25.81	25.67	25.40	26.72	**26.86**
	Im4	27.48	27.32	27.56	**27.58**	26.40	26.44	26.76	27.27	27.52
	Im5	25.97	26.00	25.77	25.40	26.16	25.28	25.40	**26.47**	26.34
	Im6	26.33	26.64	26.49	26.34	25.66	25.48	25.58	26.51	**26.65**
	Im7	26.20	26.03	26.56	26.35	25.43	25.24	25.49	26.38	**26.71**
	Im8	26.25	26.24	25.42	**26.70**	24.80	25.77	24.59	25.98	26.00
	Im9	24.59	24.69	24.74	24.65	23.67	23.50	23.91	**24.94**	24.82
	Im10	24.18	22.78	24.03	23.97	22.57	23.61	23.20	22.71	**24.22**
	Im11	25.66	**25.72**	25.00	25.56	24.54	24.28	24.36	25.58	25.69
16	Im1	26.36	26.52	26.28	**26.71**	26.12	26.33	26.67	25.79	26.66
	Im2	24.06	24.98	24.46	24.50	24.63	24.76	**25.10**	24.12	24.95
	Im3	26.43	26.84	26.54	26.54	26.16	26.37	26.21	26.72	**26.86**
	Im4	27.48	27.32	27.56	27.58	27.38	27.73	**27.79**	27.27	27.52
	Im5	25.97	26.00	**25.77**	25.40	25.80	26.22	25.66	26.47	26.34
	Im6	26.33	26.64	26.49	26.34	**26.77**	26.56	26.45	26.51	26.65
	Im7	26.20	26.03	26.56	26.35	26.64	26.56	26.65	26.38	**26.71**
	Im8	26.25	26.24	25.42	**26.70**	25.47	25.77	26.15	25.98	25.00
	Im9	24.59	24.69	24.74	24.65	**25.11**	24.76	24.48	24.94	24.72
	Im10	**24.18**	22.78	24.03	23.97	22.94	23.10	23.55	22.71	23.92
	Im11	25.66	25.72	25.00	25.56	25.68	25.61	25.51	25.58	**25.89**
20	Im1	27.71	27.57	27.76	27.40	28.15	27.61	27.77	27.75	**28.33**
	Im2	25.84	26.10	26.17	25.76	26.16	26.00	25.09	25.77	**26.46**
	Im3	27.78	**28.48**	27.68	27.93	28.45	27.85	28.24	27.73	27.96
	Im4	28.83	28.84	28.97	29.09	29.20	28.73	29.17	28.97	**29.23**
	Im5	27.54	26.78	**28.26**	27.80	27.00	26.69	26.97	27.39	28.07
	Im6	27.98	27.90	27.68	28.12	**28.42**	28.01	27.80	28.18	28.06
	Im7	28.42	28.17	28.18	28.11	27.77	27.96	28.23	28.49	**28.89**
	Im8	26.17	26.56	25.89	26.16	26.07	25.83	**27.12**	26.01	26.81
	Im9	26.34	26.45	**26.51**	26.23	26.35	26.35	26.14	25.80	26.45
	Im10	24.48	**25.90**	23.64	24.95	25.57	24.95	25.03	24.45	25.26
	Im11	27.04	27.47	26.72	27.22	27.42	27.57	27.02	27.22	**28.07**
STD.		2.9401	3.0196	3.0220	2.9999	2.9774	2.9768	2.9993	2.9878	2.8547

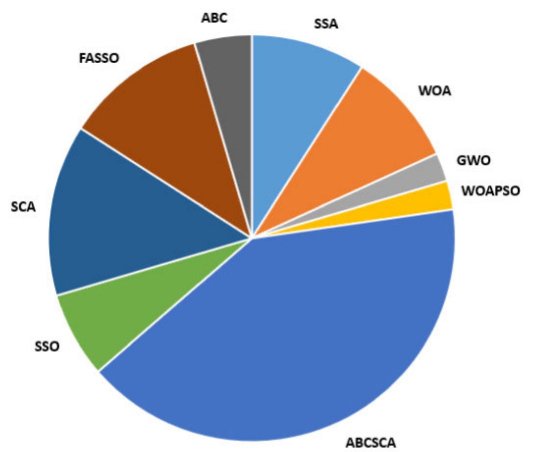

FIGURE 10. Ratio of the achievement of all algorithms based on PSNR.

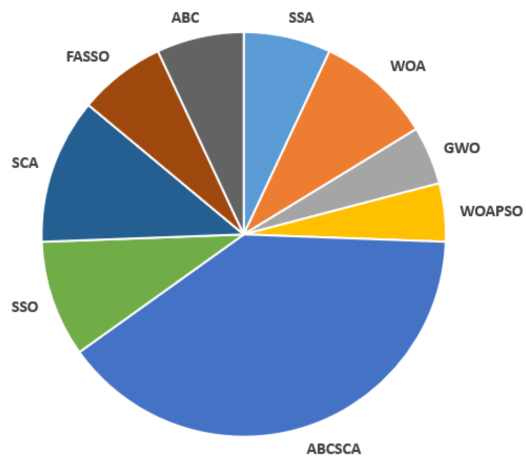

FIGURE 11. Ratio of the achievement of all algorithms based on SSIM.

overall thresholds. Whereas, the SCA is ranked second with 11% in the experiment. The WOA and SSO achieved 9% for each one and ranked third and fourth, respectively. The rest of the algorithms are ranked in this order SSA, FASSO, then ABC, respectively with 7% for each one. Whereas, GWO and WOAPSO came in the last order.

In terms of the STD, it can observed that the proposed ABCSCA has the smallest STD value in terms of PSNR and SSIM followed by the SSA algorithm. 5-4.

C. COMPARISON BETWEEN OTSU AND FUZZY ENTROPY

In this section, we evaluate the proposed method over some new images using fuzzy entropy along with otsu's methods. Figure 12 illustrate the test images and its name which taken from (https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/BSDS300/html/dataset/images.html). Table 6 shows the PSNR results at thresholds levels 6, 16, and 20. Regarding the results of Otsu's method, at level 6, the ABC-SCA outperforms other algorithms in 3 images whereas,

TABLE 5. Average of the SSIM values for all algorithm for 6, 12, 16, and 20 thresholds.

		SSA	WOA	GWO	SSO	SCA	ABC	FASSO	WOAPSO	ABCSCA
6	Im1	0.695	0.683	0.688	0.698	0.681	0.682	0.672	0.673	0.701
	Im2	0.669	0.686	0.673	0.685	0.664	0.676	0.673	0.657	0.695
	Im3	0.765	0.762	0.754	0.775	0.763	0.744	0.759	0.759	0.828
	Im4	0.635	0.633	0.640	0.628	0.638	0.627	0.638	0.630	0.666
	Im5	0.776	0.768	0.759	0.768	0.779	0.777	0.767	0.785	0.793
	Im6	0.694	0.707	0.693	0.691	0.691	0.690	0.689	0.687	0.719
	Im7	0.694	0.677	0.684	0.679	0.661	0.676	0.669	0.671	0.768
	Im8	0.705	0.696	0.693	0.678	0.698	0.700	0.687	0.705	0.722
	Im9	0.615	0.649	0.644	0.622	0.657	0.643	0.633	0.643	0.775
	Im10	0.645	0.636	0.596	0.638	0.625	0.626	0.614	0.644	0.741
	Im11	0.630	0.615	0.634	0.653	0.609	0.628	0.611	0.608	0.766
12	Im1	0.742	0.752	0.762	0.755	0.767	0.766	0.750	0.780	0.786
	Im2	0.802	0.800	0.803	0.780	0.789	0.806	0.800	0.785	0.819
	Im3	0.884	0.879	0.874	0.883	0.886	0.883	0.882	0.881	0.881
	Im4	0.783	0.777	0.775	0.775	0.769	0.754	0.777	0.765	0.779
	Im5	0.838	0.844	0.828	0.856	0.853	0.845	0.847	0.838	0.849
	Im6	0.801	0.803	0.810	0.796	0.798	0.800	0.806	0.793	0.804
	Im7	0.822	0.810	0.811	0.823	0.806	0.820	0.813	0.814	0.815
	Im8	0.802	0.803	0.796	0.803	0.804	0.815	0.805	0.804	0.807
	Im9	0.816	0.829	0.812	0.814	0.811	0.805	0.821	0.829	0.829
	Im10	0.773	0.783	0.757	0.759	0.782	0.752	0.780	0.774	0.778
	Im11	0.779	0.765	0.789	0.794	0.771	0.795	0.781	0.788	0.796
14	Im1	0.803	0.806	0.795	0.802	0.786	0.785	0.772	0.784	0.801
	Im2	0.824	0.838	0.834	0.834	0.820	0.824	0.812	0.818	0.843
	Im3	0.913	0.916	0.910	0.912	0.903	0.898	0.893	0.914	0.917
	Im4	0.828	0.826	0.828	0.811	0.807	0.805	0.809	0.815	0.827
	Im5	0.863	0.870	0.860	0.856	0.866	0.863	0.853	0.873	0.871
	Im6	0.839	0.838	0.839	0.835	0.822	0.821	0.821	0.837	0.843
	Im7	0.856	0.850	0.861	0.857	0.843	0.832	0.839	0.858	0.865
	Im8	0.843	0.844	0.829	0.857	0.823	0.841	0.816	0.835	0.842
	Im9	0.868	0.869	0.866	0.869	0.845	0.844	0.854	0.875	0.869
	Im10	0.810	0.785	0.811	0.812	0.772	0.798	0.791	0.782	0.808
	Im11	0.848	0.856	0.827	0.846	0.825	0.812	0.809	0.843	0.859
16	Im1	0.803	0.806	0.795	0.802	0.797	0.786	0.800	0.784	0.804
	Im2	0.824	0.838	0.834	0.834	0.832	0.835	0.845	0.818	0.843
	Im3	0.913	0.916	0.910	0.912	0.909	0.909	0.907	0.914	0.917
	Im4	0.828	0.826	0.828	0.811	0.816	0.824	0.835	0.815	0.827
	Im5	0.863	0.870	0.860	0.856	0.869	0.862	0.862	0.873	0.871
	Im6	0.839	0.838	0.839	0.835	0.840	0.834	0.836	0.837	0.843
	Im7	0.856	0.850	0.861	0.857	0.863	0.864	0.867	0.858	0.865
	Im8	0.843	0.844	0.829	0.857	0.831	0.835	0.843	0.835	0.846
	Im9	0.868	0.869	0.866	0.869	0.877	0.868	0.860	0.875	0.867
	Im10	0.810	0.785	0.811	0.812	0.789	0.784	0.797	0.782	0.818
	Im11	0.848	0.856	0.827	0.846	0.850	0.846	0.840	0.843	0.854
20	Im1	0.835	0.830	0.832	0.825	0.823	0.810	0.818	0.829	0.860
	Im2	0.857	0.863	0.864	0.852	0.863	0.859	0.844	0.857	0.875
	Im3	0.927	0.936	0.926	0.928	0.935	0.928	0.933	0.925	0.995
	Im4	0.858	0.868	0.861	0.856	0.866	0.855	0.860	0.858	0.866
	Im5	0.893	0.885	0.892	0.893	0.880	0.875	0.882	0.891	0.886
	Im6	0.863	0.857	0.860	0.866	0.870	0.862	0.861	0.866	0.879
	Im7	0.893	0.891	0.889	0.890	0.883	0.887	0.892	0.897	0.898
	Im8	0.841	0.853	0.835	0.848	0.848	0.835	0.862	0.848	0.858
	Im9	0.898	0.901	0.902	0.896	0.899	0.900	0.895	0.887	0.898
	Im10	0.821	0.846	0.795	0.828	0.842	0.831	0.834	0.819	0.828
	Im11	0.873	0.878	0.863	0.873	0.880	0.882	0.870	0.875	0.879
STD.		0.0759	0.0770	0.0764	0.0760	0.0773	0.0757	0.0776	0.0780	0.06037

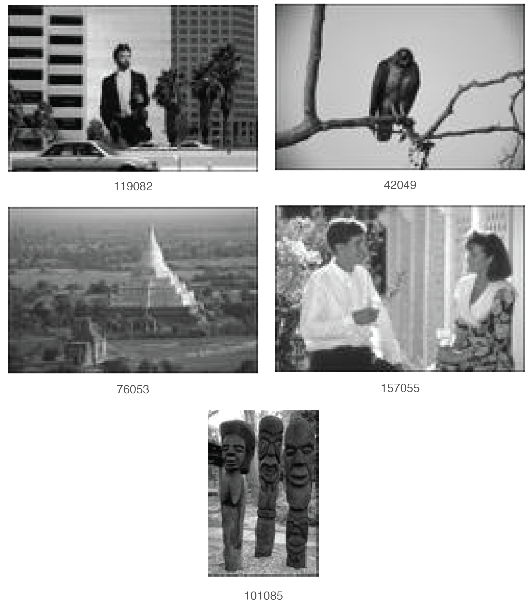

FIGURE 12. The Original of images namely 119082, 101085, 76053, 42049, and 157055.

TABLE 6. The PSNR results of the proposed method using otsu and Fuzzy entropy methods.

K	Im	Otsu								
		SSA	WOA	GWO	SSO	SCA	ABC	FASSO	WOAPSO	ABCSCA
6	119082	22.15	22.71	22.67	20.63	17.16	21.90	20.82	20.50	**23.02**
	101085	21.49	22.24	**22.29**	20.35	16.68	21.46	20.40	20.09	22.20
	76053	20.27	20.85	21.25	20.15	9.59	20.60	18.36	19.83	**22.51**
	42049	22.80	24.02	24.41	20.68	5.40	23.35	21.71	21.62	**25.45**
	157055	20.19	20.44	**20.77**	19.08	8.10	20.60	19.64	19.30	20.58
16	119082	27.99	**29.72**	29.28	26.70	17.92	28.03	26.30	26.50	29.12
	101085	28.20	29.55	29.36	26.04	17.77	28.06	26.84	26.89	**29.61**
	76053	28.83	30.66	31.21	26.06	10.50	28.28	25.00	25.29	**32.09**
	42049	28.90	31.37	30.83	26.97	5.97	29.06	26.85	25.96	**32.54**
	157055	26.74	29.61	28.95	25.12	5.93	27.76	25.19	25.10	**30.11**
20	119082	29.80	**31.52**	30.97	27.70	18.72	29.34	28.37	28.11	31.48
	101085	29.73	**31.52**	30.74	28.10	18.17	29.44	27.90	27.87	30.74
	76053	30.26	32.60	32.49	26.42	8.43	29.89	27.05	27.58	**33.09**
	42049	30.80	31.05	27.80	26.26	6.34	30.74	27.36	25.96	**33.05**
	157055	28.87	**31.27**	29.98	26.73	6.18	29.21	26.24	27.08	31.09
Avg.		26.47	27.94	27.53	24.47	11.52	26.51	24.54	24.51	28.45
K	Im	Fuzzy Entropy								
		SSA	WOA	GWO	SSO	SCA	ABC	FASSO	WOAPSO	ABCSCA
6	119082	14.98	12.83	12.33	16.92	13.32	14.57	**17.81**	17.40	17.16
	101085	14.58	13.14	12.53	17.51	15.02	14.38	15.61	16.79	**18.14**
	76053	13.51	11.53	10.48	16.56	13.52	13.44	17.77	16.63	**17.80**
	42049	15.94	14.99	12.91	17.31	12.93	15.45	16.91	15.80	**18.04**
	157055	13.70	11.73	11.44	16.95	12.75	13.78	15.30	**16.95**	16.00
16	119082	24.50	24.50	23.22	24.22	16.28	**25.53**	24.15	24.67	24.99
	101085	24.30	23.05	23.45	24.82	17.26	23.85	24.40	23.37	**25.59**
	76053	25.58	24.78	24.21	23.50	17.00	23.17	24.95	24.11	**26.37**
	42049	26.33	24.54	23.48	24.30	15.63	25.62	26.18	26.88	**26.99**
	157055	23.33	23.88	22.32	24.36	15.60	23.30	24.64	24.75	**25.15**
20	119082	25.36	25.92	25.78	26.31	17.11	25.37	**26.34**	25.66	25.90
	101085	26.13	25.95	25.83	26.55	17.27	25.54	25.81	25.44	**26.98**
	76053	27.20	26.25	26.36	26.50	17.46	27.89	25.62	26.76	**28.38**
	42049	26.78	26.54	25.90	27.62	17.47	**28.01**	26.75	27.69	27.71
	157055	26.11	25.55	25.26	26.21	15.41	25.17	24.89	26.48	**26.61**
Avg.		21.89	21.01	20.37	22.64	15.60	21.67	22.47	22.63	23.45

the GWO obtains the second rank. At level 16, the ABCSCA also outperforms the other algorithms in 3 images followed by WOA and GWO, respectively. At level 20, the WOA obtains the best PSNR results in 3 images whereas, the ABCSCA comes in the second rank with small differences.

Regarding the results of fuzzy entropy, at levels 6 and 20, the ABCSCA outperforms the other algorithms in 3 images followed by SSO. At level 16, the ABCSCA obtains the best PSNR results in 4 images and is ranked first followed by WOAPSO and FASSO, respectively. These results show that the ABCSCA can get the best threshold at level 16.

As the previous results show, the performance of the hybrid ABCSCA method is better than that of the SCA and ABC algorithms. The main reason for this superiority is that hybrid technology combines the properties of different methods. Therefore, the hybrid algorithm avoids getting stuck on a local point and increases the convergence rate. The performance of the proposed ABCSCA algorithm is also better than FASSO since the ABC algorithm can more efficiently explore the search space compared to FA. The exploitation ability of SCA is also better than social spider optimization (SSO), and the SCA has a small number of parameters compared to the SSO algorithm. All of this indicates that hybrid techniques have a high ability to find the optimal solution for image segmentation and this agrees with the expected of this type of algorithms and from other works in literature.

VI. FUTURE SCOPE

The proposed method for image segmentation can be used in the future to solve different problems and applications in terms of image processing such as analyzing the image structure, visualization, computer-aided diagnostics, computer vision, image classification, and object detection. In all applications, the quality of images is a very important issue in image segmentation. Low resolutions, lower contrast, or high noises can cause this problem. In general, when the image has low quality, there is a high probability to fall in local optima and produce wrong thresholds values. Therefore, the preprocessing of those images is a very important phase to improve the quality of that case as well as using a 2D histogram instead of 1D can be helpful at this phase. Therefore, the proposed method will be improved using the 2D histogram and evaluated over low-quality images.

VII. CONCLUSION

The multi-level thresholding approach is used to segment the image (cluster its elements) and is considered as a preprocessing step in many applications. In this paper, a new hybrid algorithm for multi-level segmentation was proposed. It draws from the advantages of both of the Artificial Bee Colony and Sine-Cosine algorithms. Moreover, it uses Otsu's method as a fitness function. The experimental results were presented to compare the proposed algorithm against the results of three methods at low threshold levels namely SCA, ABC, and FASSO over eight images as well as the results of eight methods (i.e. SSA, WOA, GWO, SSO, ABC, FASSO, and WOAPSO) at high threshold levels over eleven images besides, the results of the fuzzy entropy. According to the results, the ABCSCA algorithm achieved the best results in the low levels thresholds based on Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index (SSIM) measures. It also outperformed the other eight methods by 41% and 39% in terms of PSNR and SSIM, respectively. In the future works, the ABCSCA algorithm can be applied to other complex image segmentation problems, such as color image segmentation. Since, this problem requires to determine the threshold at different dimensions (I.e., RGB). Also, this becomes more important for different applications, including medical, galaxy, and others.

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