Journal of Information Hiding and Multimedia Signal Processing ©2020 ISSN 2073-4212
Ubiquitous International Volume **11**, Number **4**, December **2020**

An Optimizing Cross-Entropy Thresholding for Image Segmentation based on Improved Cockroach Colony Optimization

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Received March, 2020; revised August, 2020

Abstract. *Multilevel image thresholding plays a vital role in the image processing technique unique for the image segmentation of processing at higher rates, but the increasing exponentially exhaustive of its computational time when the number of desired thresholds significant. The metaheuristics algorithm is one of the most promising of effective and efficient ways of solving intractable problems. This paper adjusts one of the latest metaheuristics for the image segmentation problem based on the multilevel thresholding, the improved cockroach swarms optimization (ICSO). The experimental results are comparable with other state-of-the-art algorithms that show that the ICSO on standard benchmark images is better than the competitors.*

Keywords: Cross-Entropy Thresholding, Image Segmentation, Improved cockroach colony optimization.

1. **Introduction.** Image segmentation is a method of subdividing an image into homogeneous and disjunct sets that share similar properties, i.e., strength, color, and contours [1][2]. Image segmentation is essential for pattern recognition and computer vision in the application for object detection, surveillance, medical imaging, character recognition, and other fields [3][4]. Comparable sets regarding a particular homogeneity criterion in the image segmentation[5][6]. It usually represents the first step in the understanding and representation of images, and the results obtained by segmentation are used for further high-level methods such as extraction of features, semantic interpretation, and recognition of images and object classification [7][8]. It means that image segmentation simplifies the process of dividing an image into regions that are used for specific applications also[9]. However, when the number of desired thresholds significant, the image segmentation computational time is increasing exponentially exhaustively [5] [10]. The metaheuristics algorithm is one of the most promising of effective and efficient ways of

solving exponentially exhaustive problems[11][12]. Scholars attracted the meta-heuristic algorithms that were successfully applied in various fields, e.g., the community of engineering [13][14], transport[15][16], and industries[17][18][19]. Most meta-heuristics are inspired by animal behavior, social events and physical phenomena, such as the Genetic Algorithm (GA)[20], Ant Colony Optimization (ACO)[21], Grey wolf optimization (GWO) [22][23], Hierarchical Archive based mutation strategy (HARD-DE)[24][25] and Particle Swarm Optimization (PSO)[26][27]. Cockroach swarms optimization (CSO) is one of the latest metaheuristics that inspired by cockroach behaviors for global optimization[28]. The cockroach-inspired of the CSO algorithm has been applied successfully in the field of numerical optimization and combinatorial problem due to its accessible features to implement programs. However, the CCO algorithm uses pattern recognition, such as the optimal multilevel image thresholding, which has still been regarded humbly. This paper adjusts CSO for the image segmentation problem based on the multilevel thresholding. The thresholding techniques are fundamental and essential for the image segmentation. The multilevel thresholding is designed to establish boundaries for dividing the image into multiple regions. The individual cockroaches of CSO learn from each other and decide whether to follow or diversion. The controlling parameters are required to adjust for suitable the multilevel image thresholding issue that achieves optimal success.

2. **Improved Cockroach Swarms Optimization.** Cockroach Swarms Optimization (CSO) for global optimization is taken the inspiration from the cockroach behaviors. Cockroach colony can communicate by the pheromones for making decisions and organizing themselves [28]. Cockroaches have poor vision but a good sense of smell. Cockroach society is democratic and has no absolute leadership, so their behaviors included chasing, hunger, dispersing, ruthless. The CSO algorithm also was modeled based on these behaviors[28][29]. The behaviors of chase-swarming are used to express location status as follows.

$$x_i = \{ \begin{matrix} x_i + \tau \cdot rand(p_i + x_i), x_i \neq p_i \\ x_i + \tau \cdot rand(p_g + x_i), x_i = p_i \end{matrix} \tag{1}$$

where x_i and τ denoted the location and step of cockroach respectively, with τ is a constant value, and $rand$ is a random number $\in [0, 1]$, P_i and P_g denoted the personal best location, and global best location that are expressed as follows.

$$P_i = Opt_j \{x_j, |x_i - x_j| \leq vitual\} \tag{2}$$

$$p_g = Opt_i \{x_i\} \tag{3}$$

where $visual$ is distance perception that is a constant; $j = 1, 2, ..N, i = 1, 2, ..N$; and N is population size. The behavior of dispersion cockroaches is applied as follows.

$$x_i = x_i + rand\,(1, D)\,,\ i = 1, 2, \ldots, N \tag{4}$$

where D is dimension of problem space, and $rand(1, D)$ is a vector random $\in [1, D]$.

$$x_k = p_{g'} \tag{5}$$

The improvement version of the CSO (ICSO) is presented with a modified cockroach location with the inertial weight to chase the swarming component of the original CSO as follows.

$$x_i = \begin{cases} \omega \cdot x_i + \tau \cdot rand \times (P_i - x_i)\,,\ x_i \neq P_i \\ \omega \cdot x_i + \tau \cdot rand \times (p_g - x_i)\,,\ x_i = P_i \end{cases} \tag{6}$$

The ICSO also presented with a modified hunger of cockroach behavior by replaced Eq.(4) the original CSO with the following equation.

$$x_i = \begin{cases} x_i + (x_i - c_t) + x_{food}, \ if \ rand \leq t_{hunger} \\ x_i + rand\,(1, D)\,, \ otherwise \end{cases} \tag{7}$$

where $(x_i - c_t)$ is cockroach migration from its x_i present position, c_t is a constant that controls migration speed at the time, x_{food} denotes food location, t_{hunger} is hunger threshold, that is a random number. The ICSO algorithm is illustrated with computational steps as follows.

- *Step*1 Initialize the cockroach colony with uniformly distributed random, objective function f, dimension D, and boundaries.
- *Step*2 Calculate P and Q, according to Eqs. (2) and (3), respectively
- *Step*3 Act chase-swarming, according to Eq. (6).
- *Step*4 Put a hungry manner using Eq. (7)
- *Step*5 Perform dispersion behavior Eq.(2)
- *Step*6 Behave ruthlessly with Eq.(5).
- *Step*7 Repeat the loop until the criterion max-iteration has been reached.

3. **Image Segmentation based on ISCO.** The threshold-based scheme is one of the potent image segmentation algorithms that is to separate the object and background pixels by selecting a few thresholds. For example, the problem of bilevel thresholding must choose one limit only to divide objects and backgrounds into two classes, which is easily implemented. Multilevel thresholding is, however, more prevalent in solving challenge tasks such as mixed-type document analysis and segmentation of color images [3] [5]. This section concentrates on the issue of segmentation of the color image that can be extracted from the features based on optimization cross-entropy by the ICSO algorithm.

Assume that n thresholds for an original image can be divided into the various groups $T(n+1)$.
Let $t_1, t_2, , t_n$ be n thresholds of the image regions with $[class]_1 \in \{0, ..., t_1\}, [class]_2 \in \{t_1, ..., t_2\}, ..., [class]_{(n+1)} \in \{t_n, ..., L\}$. The objective function for the optimal n thresholds is formulated as follows

$$\begin{gathered} \{t_1^*, \ \ldots, t_n^*\} = argmin \ \{f\,(t_1, \ \ldots, t_n)\} \\ Subject \ to \ 0 < t_1 < t_2 \ < \ldots < t_n < L \end{gathered} \tag{8}$$

where $t_1^*, ..., t_n^*$ are optimal obtained results from n thresholds; $f(t_1, ..., t_n)$ is the objective function for the optimization of the multilevel image segmentation with optimum threshold values. The minimum cross-entropy scheme is used to determine the appropriate thresholds for image segmentation. The cross-entropy measures the theoretical distance of information for two on the same set of probability distributions, as Kullback suggested[30]. Let $P\{p_1, p_2, ..., p_n\}$, and $Q\{q_1, q_2, ..., q_n\}$ be two probabilistic distributions. The cross-entropy can be expressed for two distributions of the P and Q as follows.

$$D\,(P, \ Q) = \sum_{i=1}^{n} p_i \log \frac{p_i}{q_i} \tag{9}$$

The threshold values can be calculated based on optimizing the cross-entropy between the threshold version and the original image. The feature extraction of the image I_s is figured out as follows.

$$I_s\left(x,y\right)=\begin{cases} u\left(1,t\right), & I\left(x,y\right)<t \\ u\left(t,L+1\right), & I\left(x,y\right)\geq t \end{cases} \tag{10}$$

where I is the original image (with $z(i)$ is its histogram); $i = 1, 2, ..., L, L$ is a gray level); t is the threshold value for extracting feature image I, and u can be calculated as follows.

$$u\left(a,b\right)=\sum_{i=a}^{b-1} iz\left(i\right)/\sum_{i=a}^{b-1} z\left(i\right) \tag{11}$$

Then the cross-entropy can be rewritten as expression follows.

$$D\left(t\right)=\sum_{i=1}^{t-1} iz\left(i\right)\log\left(\frac{i}{u\left(1,t\right)}\right)+\sum_{i=t}^{L} iz\left(i\right)\log\left(\frac{i}{u\left(t,\ L+1\right)}\right) \tag{12}$$

Also, its expression can be expressed as follows.

$$D\left(t\right)=\sum_{i=1}^{L} iz\left(i\right)\log\left(i\right)-\sum_{i=1}^{t-1} iz\left(i\right)\log\left(u\left(1,t\right)\right)-\sum_{i=t}^{L} iz\left(i\right)\log\left(u\left(t,\ L+1\right)\right) \tag{13}$$

The extension with the case of the n thresholds can apply obtained multilevel image feature extraction that can be expressed as follows.

$$\begin{aligned}\left(t_1,\ \ldots,t_n\right)=&\sum_{i=1}^{L} iz\left(i\right)\log\left(i\right)-\sum_{i=1}^{t_1-1} iz\left(i\right)\log\left(u\left(1,t_1\right)\right)\\ -&\sum_{i=t_1}^{t_2-1} iz\left(i\right)\log\left(u\left(t_1,\ t_2\right)\right)\ -\sum_{i=t_n}^{L} iz\left(i\right)\log\left(u\left(t_n,\ L+1\right)\right)\end{aligned} \tag{14}$$

The minimum cross-entropy determines the optimal threshold values, in which adding $t_0 = 1, t_(n + 1) = L + 1$, and then the objective function can be redefined as follows.

$$f\left(t_1,\ \ldots,t_n\right)=-\sum_{k=0}^{n}\sum_{i=t_k}^{t_{k+1}-1} iz\left(i\right)\log\left(u\left(t_k,\ t_{k+1}\right)\right) \tag{15}$$

The optimal n thresholds $\{t_1^*, ..., t_n^*\}$ by the MCET can be calculated as follows. $\{t_1^*, ..., t_n^*\} = argmin\{f(t_1, ..., t_n)\}$. Fig. 1 shows the ISCO algorithm for image segmentation is illustrated with flowchart steps as follows.

4. **Experimental Results.** The multilevel thresholding segmentation of color images is optimized by the proposed method based on minimum cross-entropy as a fitness function. Six color images are selected to test the proposed scheme performance for multilevel thresholding segmentation [3][5]. The three (RGB) channels are set threshold values to 5, 8, and 11. Figure 2 lists the selected image color with each color image has different bands (RGB) with it's a multidimensional, multimodal model.

The obtained results of the proposed ISCO method for image feature extraction are compared with the PSO [27] and GWO[23] methods, respectively. Each color image channel, then the segmented results are concatenated to form the final segmented image. Figure 3 illustrates the comparison convergence of the proposed ICSO scheme with the PSO and GWO methods, and the visually extracted three channels (RGB) for image 1 with thresholds set to 5. It is seen that the proposed ICSO scheme produces the coverage faster than the PSO and GWO scheme. Figure 4 displays the visually extracted (RGB) channels of image 01 with thresholds set to 8. Figure 5 shows several visually segmented

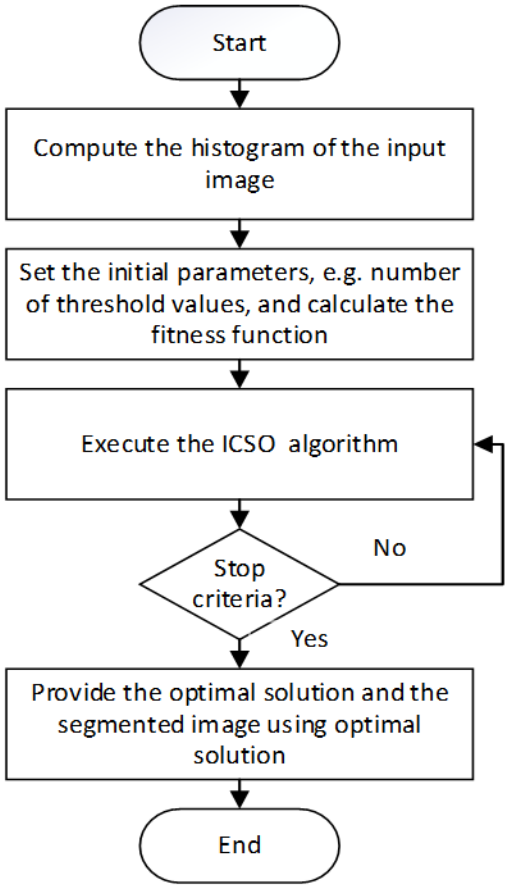

FIGURE 1. Flowchart of the multilevel image features extraction solution by applying the ISCO

FIGURE 2. The selected image color with each color image with a multidimensional and multimodal model

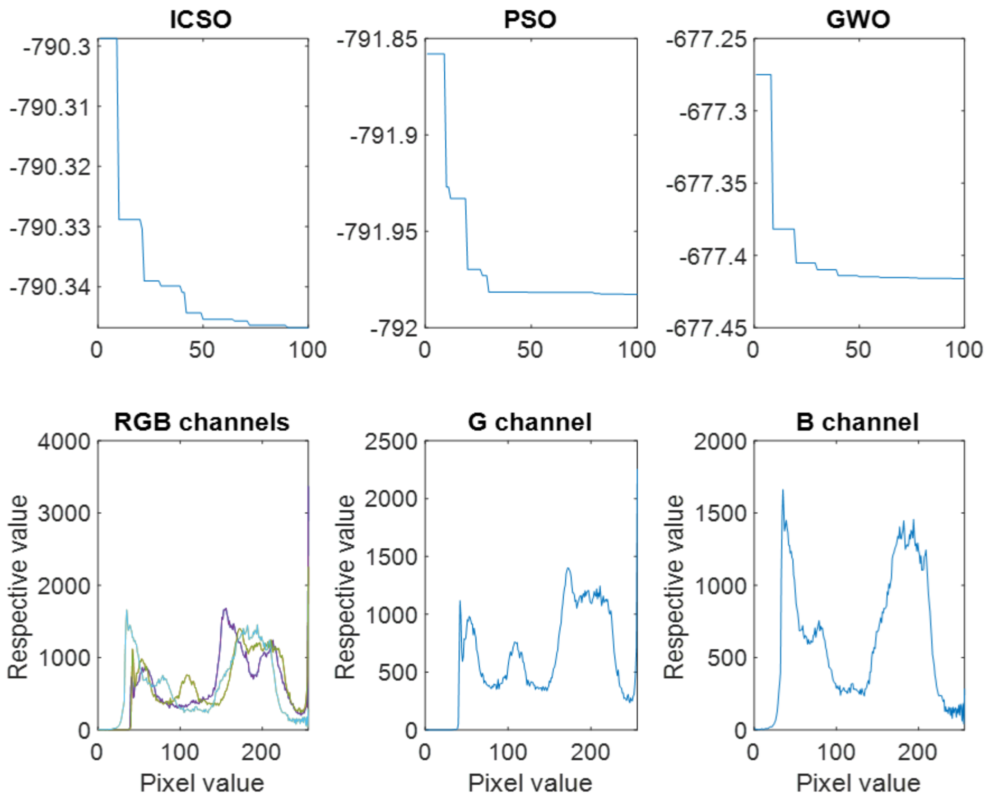

FIGURE 3. Comparison convergence of the proposed ICSO scheme with the PSO [27] and GWO [23] methods and the visually extracted three channels (RGB) for image 1

FIGURE 4. Visually extracted (RGB) channels of image 01

images after using various optimization algorithms. It indicates that the accuracy of the segmented image has improved by the proposed scheme with thresholds increase.

In order to assess the quality of the segmented image of the results obtained from the experiment, metrics of PSNR and SSIM are used to perform a comprehensive evaluation

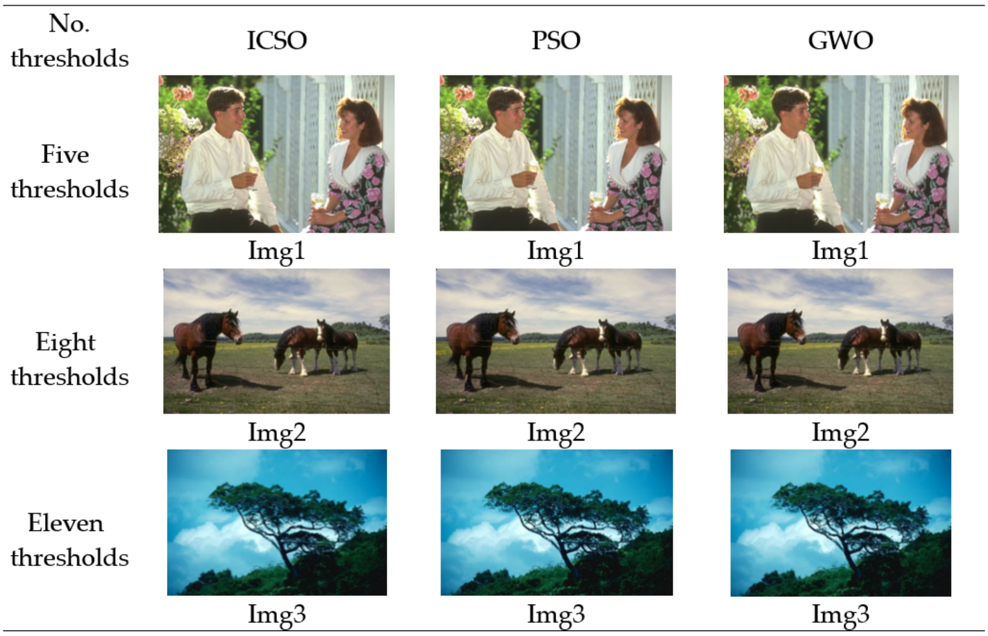

FIGURE 5. Comparison visually feature extracted of the proposed ICSO scheme with the PSO and GWO methods with different thresholds

TABLE 1. The metric of evaluation parameters used to measure segmented image results

	Parameters	Formulas	Remarks
1.	MSE and $PSNR$	$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[I(x,y) - I'(x,y)]^2$; $PSNR = 20\log_{10}\frac{255}{\sqrt{MSE}}$	MSE is a metric of the deviation between actual and expected values. $PSNR$ is the ratio between maximum signal and the noise obtained from MSE.
2.	$SSIM$	$SSIM(I,I') = \frac{(2\mu_I\mu_{I'}+C_1)(2\sigma_{II'}+C_2)}{(\mu_I^2+\mu_{I'}^2+C_1)(\sigma_I^2+\sigma_{I'}^2+C_2)}$	$SSIM$ is a parameter of structural similarity between the original image and the segmented image.

of the various algorithms in comparison. Table 1 lists the metric of evaluation parameters used to measure segmented image results.

A higher value of the PSNR, SSIM parameters, the better-segmented result is, and the segmented image quality is as good as the original image for visible. Table 2 shows a comparison of the obtained results of the optimization of the proposed scheme with PSO and GWO schemes based on a metric of the PSNR and SSIM. The best values are all highlight in Table 2. From the data values, we can see that the number highlight of the achieve identical segmented effects in six color images belongs to the proposed scheme. The proposed ISCO algorithm generally indicates better than the other contrasting algorithms. Overall, the proposed ISCO algorithm is valid and practicable in solving the problem of multilevel image segmentation.

5. **Conclusion.** This paper presented one of the latest metaheuristics the improved cockroach swarms optimization (ICSO), for the image segmentation problem based on the multilevel thresholding. The parameters of the optimization method were adjusted to suit the multilevel thresholding issue. Because of challenging tasks such as mixed-type

Table 2. Comparison of the obtained results of the optimization of the proposed scheme with PSO and GWO schemes for multilevel image segmentation based on a metric of the PSNR and SSIM

Images		ICSO	PSO	GWO	ICSO	PSO	GWO
		PSNR			SSIM		
Img1	5	**26.607**	26.148	26.082	**0.758**	0.756	0.756
	7	29.566	29.585	29.516	0.807	**0.808**	0.808
	11	**32.340**	31.857	31.972	**0.840**	0.839	0.838
Img2	5	**27.926**	27.928	27.862	**0.828**	0.828	0.828
	7	31.018	31.358	31.164	0.854	0.857	0.856
	11	**34.411**	33.617	33.009	**0.874**	0.870	0.870
Img3	5	**27.295**	27.297	27.231	**0.793**	0.793	0.793
	7	**30.717**	30.679	30.561	0.841	0.840	0.840
	11	32.732	33.016	**33.236**	0.857	0.864	0.854
Img4	5	**28.024**	28.025	27.959	**0.777**	0.777	0.777
	7	**31.208**	30.912	31.065	0.831	0.825	0.830
	11	33.173	**33.704**	33.630	0.847	0.855	0.855
Img5	5	28.575	28.569	28.503	0.805	0.805	0.805
	7	31.579	31.172	31.380	**0.834**	0.833	0.835
	11	33.574	33.786	33.946	0.851	0.855	0.854
Img6	5	26.439	26.429	26.359	**0.817**	0.817	0.817
	7	29.705	29.569	29.561	**0.857**	0.854	0.854
	11	32.211	32.074	31.768	0.870	**0.871**	0.869

document analysis and segmentation of color images, it is the increasing exponentially exhaustive of its computational time when the number of desired thresholds significant. The threshold-based was used to separate the object, and background pixels for the robust image segmentation is modeled for the fitness function of optimization. The ICSO was applied to deal with this problem. The experimental results were compared with other state-of-the-art algorithms that show that the ICSO on selected images is better than the competitors.

Acknowledgments. This work was supported in part by the project CS20.07 of the Institute of Information Technology, the senior mission NVCC02.01/20-20, the project VAST01.07/19-20 of the Vietnam Academy of Science and Technology.

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