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An Optimal Thresholds for Segmenting Medical Images Using Improved Swarm Algorithm

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Abstract. *The key to threshold segmentation is selecting the thresholds that will determine the segmentation's outcome—as the number of thresholds increases, the calculation complexity increases, posing issues for traditional methods. This paper presents an improved swarm algorithm method (ISA) for determining the best image segmentation thresholds. The objective function is modeled to be the global optimization issue of the segmentation function based on its entropy. The ISA works well with picture segmentation, resulting in remarkable computing in terms of global convergence and resilience and preventing local optimization trapping. It is incredibly well adapted to solving complex functions with multiple peaks and large dimensions. According to thorough theoretical study and simulation findings, in multi-image and multi-thresholds segmentation, the ISA has more efficacy, efficiency, stability of the range of thresholds, and quality than the swarm algorithm (PSO) and differential evolution (DE).*
Keywords: Improved Swarm Algorithm;Picture threshold segmentation; Optimization algorithms; Kapur entropy.

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1. **Introduction.** The image pictured is an important way for humans to receive, process, and transmit information [1]. Because of its intuitive, easy-to-understand image and the huge amount of information, image information is also one of the most indispensable and efficient information acquisition and communication methods in people's lives and production processes [2]. Image segmentation approaches, which partitions an image into homogeneous sections or groups, play a crucial technique in picture processing [3], e.g., pattern recognition, image, video processing, and retrieval. The method addresses the technology and process of splitting the gathered image into several specific regions with unique properties and extracting useful or exciting objects, which is the most effective method to help people get valuable information[4].

Several segmentation methods based on diverse concepts, such as thresholding strategies, parametric or non-parametric approaches, have been proposed in the literature. The introduction of thresholding tactics for discriminating items from background images or discerning objects of different gray levels has recently supported the creation of the most recent successful ways for separating (segmenting) various photos [5]. Two or more thresholds limit gray levels in pixels from the same component. The thresholds, often found in the gray-level histogram's inflection point [4], can be discovered using parametric approaches.

The research of image segmentation technology has been involved in many fields [6]. Its in-depth analysis and final solution can significantly promote the development and maturity of many disciplines. Many studies have been carried out at home and abroad in recent years, and new segmentation techniques and methods have emerged endlessly [5][7]. However, there is still no universal segmentation theory. The image segmentation algorithms include several types, such as region-based, threshold-based, edge-based segmentation approaches, and image segmentation algorithms combined with other specific views [8].

The threshold segmentation method is the most specific used way in image segmentation. A variety of methods of image segmentation is implemented. Still, due to the variety of images and the uncertainty of image data, no general image segmentation algorithm can accurately segment any image. Some algorithms can directly segment general images, while others can only segment some specific images.

By selecting the appropriate segmentation threshold, the target and non-target in the image are segmented to provide the basis for the follow-up work [9]. The optimization algorithms are based on artificial intelligence[10]. e.g., generic intelligence (GA)[11], Differential evolution (DE)[12][13], Bats algorithm (BA)[14][18] and swarm intelligence (PSO) [15] [16] can deal with nonlinear optimization problems faster, more accurately, and stably [17].

This study suggests an improved swarms algorithm (ISA) based on the particles swarm algorithm (PSO) for selecting optimal picture segmentation thresholds. The global optimization issue of the segmentation function's objective function is modeled based on Kapur's image entropy. The strategy of group communication and inertia weight is used to improve the algorithm to better solve the optimal picture segmentation thresholds problem.

The optimal threshold value determines the obtained results from ISA process optimization to achieve successful image segmentation. The algorithm applied to image segmentation can quickly select the appropriate threshold to make the segmentation effect better, improve the segmentation efficiency and segmentation accuracy, which is conducive to efficient follow-up work. The simulation result shows the superior performance of the suggested approach.

2. **Entropy Method for Image Segmentation.** Entropy standard method [18] is a nonparametric threshold optimization method that is an effective segmentation technology based on entropy threshold transformation technique using probability distributed histogram [3]. When the optimal threshold of the separation class is assigned correctly, the entropy is maximum. The image entropy measures the compactness and separation among image classes to find the optimal entries to generate max entropy.

The luminance level L is taken from each component of a grayscale image or the color (red, green, blue) image with RGB. The probability distributed brightness values are computed the following formula.

$$P_{h_i^a} = \frac{h_i^a}{NP}, a = \begin{cases} 1, 2, 3, \ if \ is \ color \ image \\ 1, \ if \ is \ scale \ gray \ image \end{cases}, and \sum_{i=1}^{NP} P_{h_i^a} = 1 \tag{1}$$

Here i and a are a specific brightness level with the value range of $0 \leq i \leq L-1$; and the image component; a depends on a luminance value of gray image or color image; the total number NP is the images pixels; (histogram)h_i^a is the number of pixels of brightness level i in luminance value a; histogram is the standardized probability distribution $P_{h_i^a}$. The definition of multiple classes (multi-level) is as follows.

$$\begin{aligned} C_1 &= \frac{P_{h_i^a}}{\omega_0^a(th)}, \ldots, \frac{P_{h_{th1}^a}}{\omega_0^a(th)} \\ C_2 &= \frac{P_{h_{th1+1}^a}}{\omega_1^a(th)}, \ldots, \frac{P_{h_{th2}^a}}{\omega_1^a(th)} \\ &\ldots \\ C_k &= \frac{P_{h_{thi+1}^a}}{\omega_{k-1}^a(th)}, \ldots, \frac{P_{h_{thi+1}^a}}{\omega_{k-1}^a(th)} \end{aligned} \tag{2}$$

Where $\omega_0(th), \omega_1(th)...\omega_(k-1)(th)$ are the probability distribution of C_1, C_2, and C_k is calculated by a given equation (3).

$$\begin{aligned} \omega_0^a(th) &= \sum_{i=1}^{th_1} P_{h_i^a} \\ \omega_1^a(th) &= \sum_{i=th_1+1}^{th_2} P_{h_i^a} \\ &\ldots \\ \omega_{k-1}^a(th) &= \sum_{i=th_k+1}^{L} P_{h._i^a} \end{aligned} \tag{3}$$

Based on Kapur entropy, it is necessary to divide the image into k classes by the similarity number of threshold. Therefore, the objective function is expressed as follows.

$$f(T_H) = \sum_{i=1}^{k} H_i^a, a = \begin{cases} 1,2,3 \ if \ colorRGB \ image \\ 1 \ if \ scale \ gray \ image \end{cases} \tag{4}$$

Where $T_H = [th_1, th_2, ..., th_(k+1)]$ is a vector of threshold values; The corresponding threshold's entropy can be computed as following formula.

$$\begin{aligned} H_1^a &= \sum_{i=1}^{th_1} \frac{P_{h_i^a}}{\omega_0^a(th)} \ln\left(\frac{P_{h_i^a}}{\omega_0^a(th)}\right) \\ H_2^a &= \sum_{i=th_1+1}^{th_1} \frac{P_{h_i^a}}{\omega_1^a(th)} \ln\left(\frac{P_{h_i^a}}{\omega_1^a(th)}\right) \\ &\ldots \\ H_k^a &= \sum_{i=th_k+1}^{L} \frac{P_{h_i^a}}{\omega_{k-1}^a(th)} \ln\left(\frac{P_{h_i^a}}{\omega_{k-1}^a(th)}\right) \end{aligned} \tag{5}$$

The probability values $\omega_0^a, \omega_1^a, ..., \omega_(k-1)^a$ is obtained by Eq.(3). Finally, we need to use Eq. (6) for separating pixels in the respective classes. According to the gray level (L), its threshold conversion is a process of dividing pixels into sets or classes. In classification process, selected threshold (th) in following multi-level threshold conversion formula criteria is expressed as follows.

$$\begin{gathered} C_1 \leftarrow p; \ range \ or \ if \ 0 \le p < th_1 \\ C_2 \leftarrow p; \ range \ th_1 \le p < th_2 \\ \ldots \\ C_i \leftarrow p; \ range \ th_i \le p < th_{i+1} \\ \ldots \\ C_n \leftarrow p; \ range \ th_n \le p < L-1 \end{gathered} \tag{6}$$

In formula, p is a point or pixel of the given image I_g with $m \times n$ pixels; , which represents the level in L gray level, $L = 0, 1, \ldots, L-1$; C_i is the class of pixel p, with different thresholds $th_1, th_2, ..., th_k$. The problem of multi-level or multi threshold transformation is to select the correct threshold th of recognition classes. Kapur method of entropy is to determine the thresholds that is modeled as the objective function. The proposed objective function is optimized by maximizing to find the best threshold. Eq. (7) is used for finding the k-dimensional optimal threshold and maximizing the Kapur's objective function.

$$th = \text{argmax}\left(\sum_{i=0}^{k-1} \omega_i^a\,(\text{th})\right) \tag{7}$$

3. **Improved Swarms Algorithm.** In this section, we present an improved swarms algorithm (ISA) as an optimization algorithm [19]. First, we would review the original swarm algorithm (PSO) as the birth and fish's school inspiration[20]. Second, an improved swarms algorithm is presented as follows.

3.1. **Original swarm optimization algorithm.** Kennedy and Eberhart [6] proposed the particle group optimization technique, whose primary principle is to randomly initial a group of swarms with vector particles and then move forward in discovering the optimal solution based on the fitness values by continuous iteration. The particle updates the individual and global extremism by the fitness values over iterations for its moving speed and position. The following is the basic process of the original particle group in solution matrix of the optimization algorithm. The population initialization is depicted as follows.

$$X_{(i,j)}^0 = X_j^m in + U(0,1) \times (X_j^m ax - X_j^m in) \tag{8}$$

where $X_(i,j)^0$ represents the solution of the partcles location with j dimension and initialized i particles; $U(0,1)$ represents the random generating in normal uniform distribution on range (0,1); $X_j^m in$ and $X_j^m ax$ represents the minimum and the maximum of population in searching space. The objective function is a modeled mathematical of the target solving issues. The objective function values are calculated and compared to the previous generation, updating the individual optimal value P_{best} and the global optimal value P_{best}. The particles' velocity or speed and position are updated as the principles. The particles update their search speed and position according to the fitness value of the target function, moving towards the global optimal particle after each iteration. The following formula is given specifically.

$$V_{(i,j)}^{(t+1)} = V_{(i,j)}^t + c_1 r_1 (P_{(i,j)} - X_{(i,j)}^t) + c_2 r_2 (g_j - X_{(i,j)}^t) \tag{9}$$

$$X_{i,j}^{t+1} = V_{i,j}^{t+1} + X_{i,j}^t \tag{10}$$

In the fomula, $X_{i,j}^t$ and $V_{i,j}^t$ respectively represent the positions and velocities of the i (where $i = 1, 2, 3, ..., N$) particles in its j dimension with ($j = 1, 2, 3, ..., M$); $P_{i,j}$ represents the optimal value of the particle$_i$ in dimension j; g_j represents the global optimum; c_1, c_2 represents the learning factor; r_1, r_2 represents the random number as a distributed random as normal distribution on range (0,1). The algorithm's terminated condition is determined whether the max-number of iterations is reached or other algorithm termination conditions are reached target, and the global optimum is output.

3.2. **Algorithmic Improvements.** Population diversity, dynamic inertia weight, and learning factor are three tactics introduced in this subsection to improve the swarm algorithm's performance.

Improving population diversity is introduced to implement the swarm diversity because subtraction-based solutions quickly lack particle population variety and halt the search process in traditional particle group optimization methods. Particle operation is

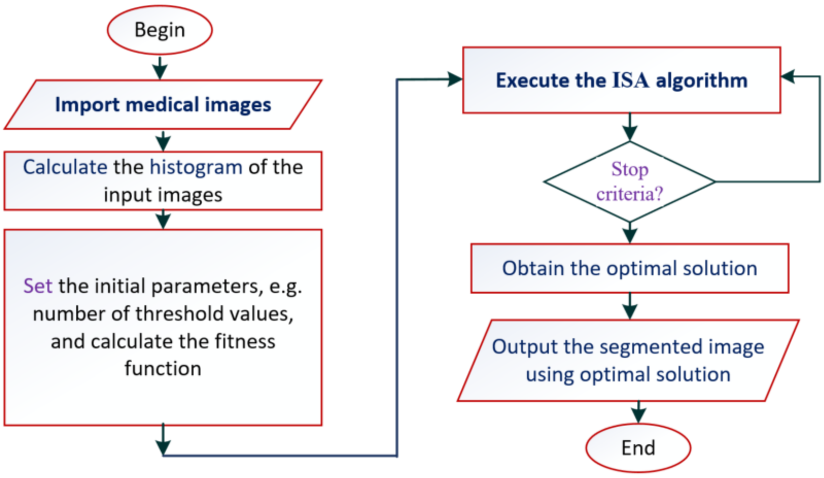

FIGURE 1. Flowchart of the ISA for image segmentation thresholds

influenced by individual and group experience, according to its updating formula. Assume a particle is in the best possible proper position according to the objective function value. The other particles could be soon approaching it in that instance. Suppose the optimal circumstance is optimal local extreme. In that case, the particle solution will quickly fall into local optimum and search in the resolution of the problem space, resulting in the algorithm's precocious phenomena. We apply a technique to overcome precocious convergence and improve population diversity as follows. Suppose the global extremum remains unchanged after the iterative operation. In that case, the historically optimal location of m ($m \leq 5\%N$) individuals are selected to regroup with the contemporary generated particles as shown in the following formula.

$$h_{new}\left(x_i\right) = (1-c) \cdot h_{old}\left(x_i\right) + c \cdot \left|h_{up}\left(x_i\right) - h_{old}\left(x_i\right)\right| \tag{11}$$

where, h_{new} represents new particles; h_{old} represents the historical optimal location selected; h_{up} represents contemporary particles; c represents the random number between $(0,1)$. The newly generated particles have different operating directions and velocities, we need to explore potential optima in new searching space, or escape the local optimum, and avoid precocious convergence. Moreover, the use of historical optimum is to reference the best position searched by the individual, it is conducted the search around it to search for a better position, then it is conducive to continuously enhancing the quality of the solution and ensuring its optimal accuracy on the basis of increasing particle diversity.

A dynamic inertia weight strategy is presented with inertial weight ω reflects the effect of the previous particle velocity on the generation [9], A usually enlarged problem in the early stage of the algorithm optimization is conducive to global optimization and small in the late iteration, conducive to local optimization. The presented strategy would be figured out as the inertia weight ω is formulated as follows.

$$\omega\left(t\right) = (\frac{\omega_{max} - \omega_{min}}{\sqrt{2\pi}}).\exp\left(-\frac{t}{T}(\omega_{max} - \omega_{min})^2\right) \tag{12}$$

In formula, ω_{max} and ω_{min} represent the maximum and minimum of inertia weights; t represents current number of iterations; T represents the max- number of iterations. The particle search capability is enhanced by adding an inertial weight ω , as shown in the following formula.

$$V_{(i,j)}^{(t+1)} = \omega V_{(i,j)}^{t} + c_1.r_1.(P_{(i,j)} - X_{(i,j)}^{t}) + c_2.r_2.(g_j - X_{(i,j)}^{t}) \tag{13}$$

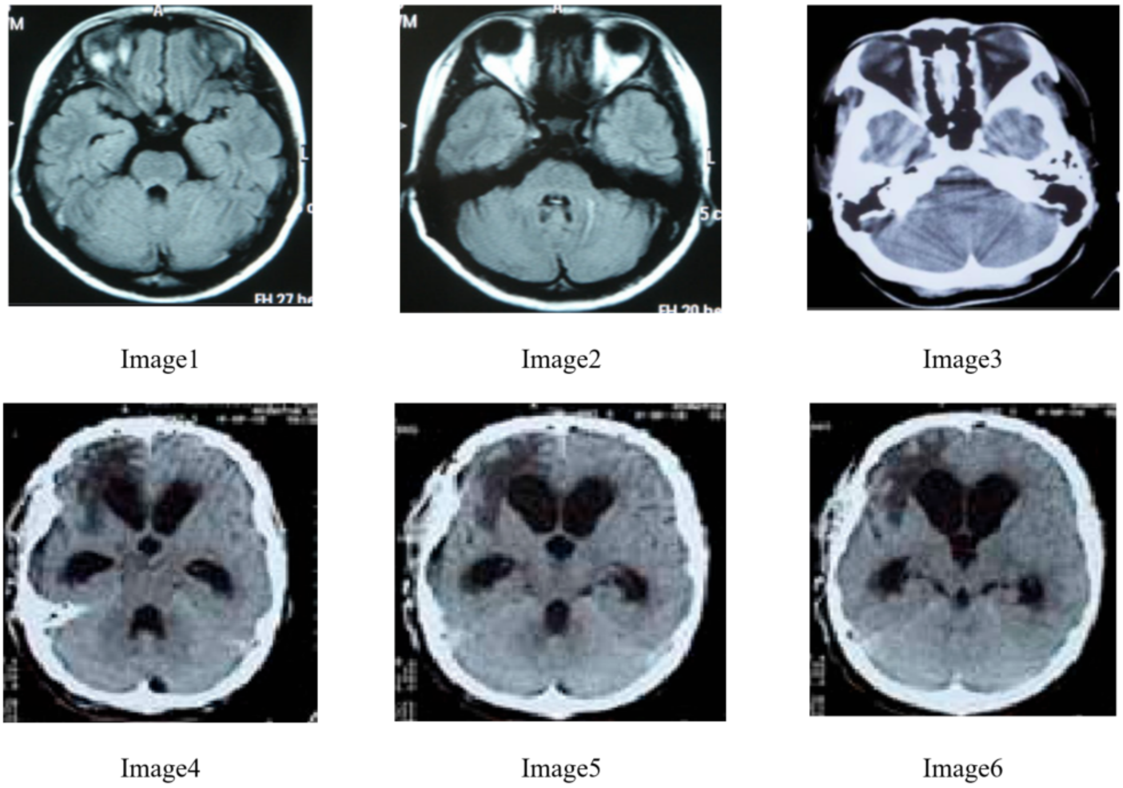

FIGURE 2. The several selected medical scan images

Unlike linear decreasing models, the formula Eq. (5) is a dynamic inertia weight of a concave function model, and the decreasing speed more matches the particle search process and better balances the algorithm's global and local optima search capability.

The learning factor is one of the impacting parameters for affecting the algorithm performance. As in many algorithm improvements, only the parameter ω on the particle operation is considered, while the learning factors' role seems to be ignored. So, c_1 and c_2 represent the effect of the particle itself velocity and another particle velocity on the current operating velocity. In the standard swarm optimization algorithm, the learning factor: c_1 and c_2 are set to the same constant for individual and group information throughout the iteration. Modifying the learning factor over the iteration process, we change the paremter c_1 decrease and c_2 increase. In the early iteration, the particles are mainly affected by individual information, which helps increase population diversity; in the later iteration, mainly affected by the group information, which allows the particles solution quickly close to the global extremal and obtains the optimal solution. The improved c_1, c_2 are shown as follows.

$$c_1\left(t\right) = 1 - \ln 2 \cdot \left(\frac{t}{T}\right) \tag{14}$$

$$c_2\left(t\right) = 1 + \ln 2 \cdot \left(\frac{t}{T}\right) \tag{15}$$

In the formula, t and T are the current number and the max number of iterations.

4. **ISA for Medical Image Segmentation.** This section presents an application of the ISA to optimal threshold vector in image segmentation by minimizing the objective

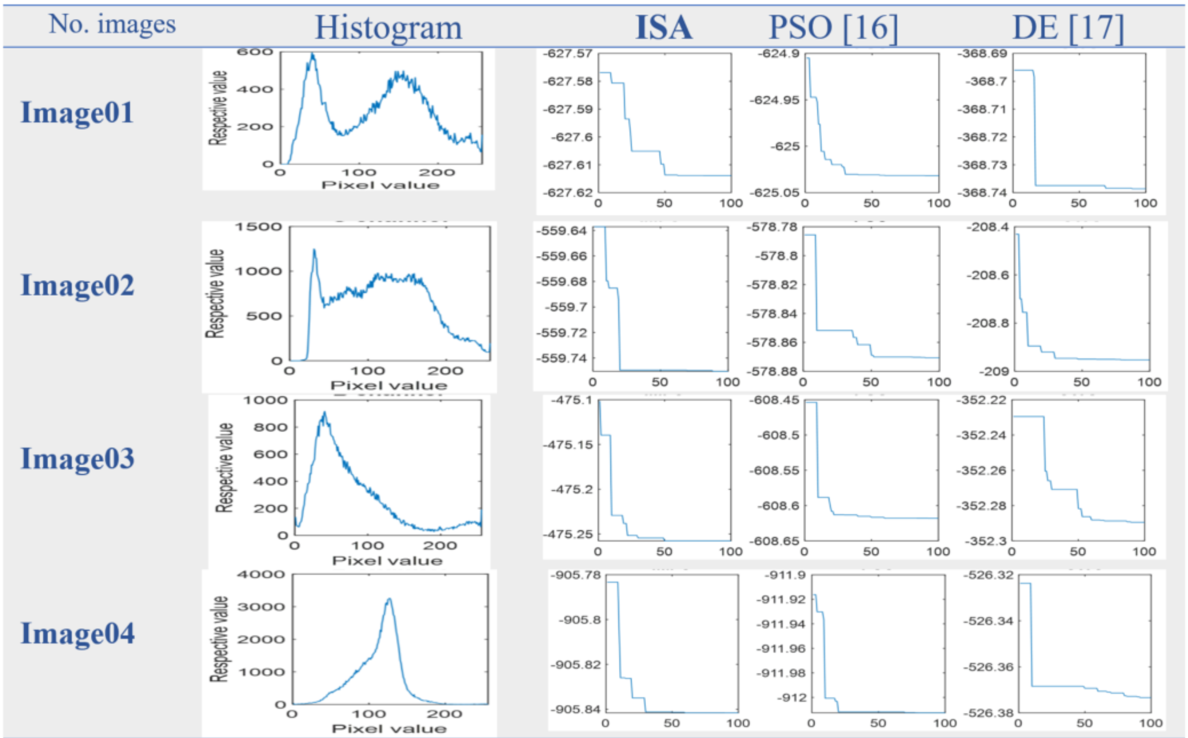

FIGURE 3. Visually compared convergence of the suggested ISA approach with the PSO and DE schemes for the medical images of mri scan scanned for 01, 02, 03 and 04 images with threshold set at 4.

function of its image cross-entropy. Figure 1 shows a flowchart of the ISA for image segmentation thresholds. The majority of steps of the ISA for image thresholds segmentation are listed as follows.

Step 1: Import the image I for judgment; calculate the image's histogram and its probability distribution.

Step 2: Generate the particle's population initialization randomly and the parameters, e.g., frequencies, Max-iteration, space dimension.

Step 3: calculate the fitness function by taking its entropy function for each particle.

Step 4: Arrange the objective function's value, assign the location of the best search, and then update the current particle's location.

Step 5: Check termination condition; go Step 3 if it is not true; otherwise, Step 6.

Step 6: output the optimal segmentation threshold.

5. **Experimental Results.** The ISA algorithm is tested through modeling the fitness function with entropy function 6 images. The obtained results from the ISA are compared with the DE [17] and PSO [16] to avoid the randomness of the results and probability distribution inappropriate statistical measures effectiveness of these algorithms. Therefore, all algorithms execute 25 times for each graph, and test threshold th is set to 2, 3, 4, 5 according to reference. The stopping criterion of each experiment is 150 iterations, NP = 50. To verify stability, the standard deviation *(STD.)* is calculated at the end of each test according to Eq. (15).

$$STD. = \sqrt{\sum_{i=1}^{Maximum\_iter} \frac{(\theta_i - \varepsilon)^2}{Maximum\_iter}} \tag{16}$$

TABLE 1. Experimental results of the ISA for the chosen medical images.

No. Images	*k*	No. Thresholds	PSNR	STD.	MSE
Image01	2	8, 89	14.267	0.712	14.211
	3	24, 45, 125	20.809	1.123	20.123
	4	23, 52,104, 145	19.696	1.453	24.973
	5	39,76,120,145,189	22.404	1.653	29.348
Image02	2	24, 123	13.421	1.103	14.232
	3	64, 120, 165	16.865	0.453	21.234
	4	43,75,120,172	19.897	1.234	25.121
	5	45,89,123,156,187	21.234	1.523	29.342
Image03	2	67, 142	15.451	0.723	16.232
	3	35,101,151	18.862	0.453	22.254
	4	41, 76, 102,165	20.897	0.834	26.121
	5	23,56, 87, 121, 186	22.234	0.952	29.042
Image04	2	8, 89	14.267	0.712	14.211
	3	24, 45, 125	20.809	1.123	20.123
	4	23, 52,104, 145	19.696	1.453	24.973
	5	39,76,120,145,189	22.404	1.653	29.648
Image05	2	24, 123	14.421	1.1023	14.232
	3	64, 121, 165	17.865	0.453	21.234
	4	43,75,120,172	19.997	1.234	25.121
	5	45,89,123,156,187	22.234	1.523	29.352
Image06	2	67, 142	15.451	0.723	16.234
	3	35101151	19.862	0.453	23.254
	4	41, 76, 102,165	21.897	0.834	25.121
	5	23,56, 87, 121, 186	22.235	0.952	28.042

In addition, the peak signal to noise ratio (PSNR.) compares the similarity between the image (image segmentation) and the reference image (the original image) according to the mean square error (MSE.) of each pixel.

$$PSNR. = 20log_{10}\left(\frac{255}{MSE.}\right) \tag{17}$$

Among them, I_0^a is the original image; I_{th}^a is the segmented image; a depends on the image; r_o and c_o are the total number of rows and columns of the image respectively.

$$MSE. = \sqrt{\frac{\sum_{i=1}^{r_o}\sum_{j=1}^{c_o}\left(I_0^a\left(i,j\right) - I_{th}^a\left(i,j\right)\right)}{r_o \times c_o}} \tag{18}$$

The Kapur entropy function is modeled for the objective function to analyze the performance of the ISA. Fig.2 shows the selected original images.

Table 2 compares the experimental segmentation results of the proposed ISA scheme with PSO and DE[17]. The methods need to run 25 times for each image, and the objective function obtained with the Kapur entropy function is calculated for each image for the average obtained values as the mean square error (MSE.), the peak signal to noise ratio (PSNR.), the standard deviation (STD.).

Table 2 shows the comparison of the image segmentation results of the ISA with the DE [17] and PSO [16] schemes. Fig. 2 shows a visually derived comparison of the suggested ISA scheme with the PSO and DE schemes for the images 01 to 04 with thresholds set at 4. The result shows that the suggested ISA approach achieves improved picture

Table 2. Comparison of the segmentation results of the ISA with PSO and DE schemes

No. Images	k	ISA			PSO[16]			DE [17]		
		PSNR	STD	MSE.	PSNR	STD.	MSE.	PSNR	STD.	MSE.
01	2	14.267	7.12E-01	14.211	11.834	1.26E-01	15.203	12.075	9.86E-02	15.830
	3	20.809	1.12E+00	20.123	14.694	2.12E-01	20.415	14.983	1.09E-01	20.808
	4	19.696	1.45E+00	24.973	17.012	2.83E-01	24.049	17.730	1.97E-01	24.674
	5	22.404	1.65E+00	29.348	19.617	3.50E-01	28.071	20.649	2.69E-01	27.940
02	2	13.421	1.10E+00	14.232	12.223	4.86E-03	15.977	12.160	3.25E-03	16.662
	3	16.865	4.53E-01	21.234	14.860	1.09E-01	20.732	14.906	3.84E-02	20.161
	4	19.897	1.23E+00	25.121	16.935	2.57E-01	23.357	17.570	1.78E-01	24.082
	5	21.234	1.52E+00	29.342	19.373	3.02E-01	26.968	20.135	2.15E-01	27.113
03	2	15.451	7.23E-01	16.232	12.074	5.62E-02	16.277	12.030	7.58E-03	16.559
	3	18.862	4.53E-01	22.254	14.612	1.57E-01	20.879	14.783	8.04E-02	20.772
	4	20.897	8.34E-01	26.121	16.783	1.75E-01	25.260	17.310	8.40E-02	24.009
	5	22.234	9.52E-01	29.042	19.485	2.75E-01	29.335	19.921	1.87E-01	30.529
04	2	14.267	7.12E-01	14.211	10.376	8.64E-02	15.342	13.890	2.46E-03	13.887
	3	20.809	1.12E+00	20.123	11.523	2.00E-01	19.862	12.128	1.85E-01	19.050
	4	19.696	1.45E+00	24.973	13.194	2.57E-01	23.764	14.018	2.44E-01	24.812
	5	22.404	1.65E+00	29.648	15.614	3.94E-01	27.164	16.092	2.78E-01	26.599
05	2	14.421	1.10E+00	14.232	13.384	7.18E-02	18.354	13.264	1.18E-03	18.352
	3	17.865	4.53E-01	21.234	15.014	1.54E-01	22.945	14.793	5.22E-02	13.060
	4	19.997	1.23E+00	25.121	15.766	2.67E-01	26.557	15.596	1.40E-01	27.058
	5	22.234	1.52E+00	29.352	16.769	8.89E-01	30.574	16.074	4.91E-01	30.786
06	2	15.451	7.23E-01	16.234	14.153	8.09E-02	18.584	14.131	1.97E-04	18.314
	3	19.862	4.53E-01	23.254	8.189	1.97E-01	23.051	16.695	1.70E-01	22.940
	4	21.897	8.34E-01	25.121	14.900	2.67E-01	26.294	18.113	2.44E-01	26.996
	5	22.235	9.52E-01	28.042	18.834	9.65E-01	30.521	19.551	6.07E-01	30.819

segmentation quality better the DE [17] and PSO [16] schemes that are clear advantages over DE and PSO in terms of running time and convergence.

6. **Conclusions.** This paper proposed an improved swarms algorithm (ISA) for selecting optimal multi-level threshold image segmentation. The Kapur entropy function has been modeled for the global optimization issue of the segmentation function's objective function. The objective function has been analyzed and processed in the multi-threshold image segmentation field by the ISA's performance. Compared with the other schemes, e.g., differential evolution (DE) and particle swarms' algorithm (PSO), the proposed ISP approach achieves improved picture segmentation quality. It has clear advantages over DE and PSO in terms of running time and convergence.

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