Multi-Level Thresholding for Image Segmentation With Swarm Optimization Algorithms

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***Abstract*—Image segmentation is an important problem for image processing. The image processing applications are generally affectedfromthe segmentation success. There is noany image segmentation method which gives good results for all sorts of images. That's why there are many approaches and methods forimage segmentationin the literature. And one of the most used is the thresholding technique. Thresholding techniques can be categorized into two topics: bi-level and multi-level thresholding. Bi-level thresholding technique has one threshold value which separates the image into two groups. However, multi-level thresholding technique uses *n* threshold values where *n* greater than one. In this paper, two swarm optimization algorithms (Particle Swarm Optimization, PSO and Cat Swarm Optimization, CSO) are applied on finding the optimum threshold values for the multi-level thresholding. In literature, there are some minimization or maximization functions to find the best threshold values for thresholding problem. Some of these methods are: Tsalli's Entropy, Kapur's Entropy, Renyi's Entropy, Otsu's Method (within class variance/between class variance), the Minimum Cross Entropy Thresholding (MCET) etc.In this work, Otsu's (within class variance) method, which is one of these popular functions,is used as the fitness function of algorithms.In the experiments, five real images are segmented by usingParticle Swarm Algorithm and Cat Swarm Optimization Algorithms. The performances of the swarm algorithms on multi-level thresholding problem arecompared with Peak Signal-to-Noise Ratio (PSNR) and fitness function (FS) values. As a result, the PSO yields better performance than CSO.**

***Keywords:* image segmentation, thresholding, otsu, within class variance, cat swarm optimization, particle swarm optimization**

I. INTRODUCTION

Image segmentation is a very important task whichdivides a given image into meaningful and homogeneous regions[1].The aim of the image segmentation is reducing and simplifying the presentation of the image for easier analysis. The segmentation process separates the pixels of the image into different groups according to their similarities [2-4]. In the literature, there are many segmentation methods which have been proposed and developed by researchers Thresholding technique is one of the most popular, simple and effective segmentation method among all existing techniques.

Its accuracy, simplicity and robustness make it so popular when compared with other available techniques in the literature [5-8].Thresholding techniquescan be categorized as bi-level and multi-level thresholding. Bi-level thresholding technique has one threshold value which separates the image into two groups. Multi-level thresholding technique uses*n* threshold values where *n* greater than one[7, 8]. The approachesare used to find optimum threshold values are classified into two groups: *Parametric* and *nonparametric approaches*. The parametric approaches estimate the statistical parameters of the image. As well, these approaches have high computation time and sensitive performance depends on the initial state. On the other hand, nonparametric approaches need the number of threshold. The main purpose of these approaches is to determine the optimal threshold values by finding the minimum (or maximum) value of the relative objective function[9]. Otsu's method is a popular method whichis used as the objective function to determine the best threshold values. In this method, the optimal thresholds are foundwith maximizing ofthe between-class variance or minimizingof the within-class variance of the regions which are labeled as thresholds [5, 10].

In recent years, meta-heuristic optimization approacheshave been widely used in multi-levelthresholding issue to find significant solutions for image segmentation problem. An efficient cuckoo search*(CS)* algorithmwasapplied to solve the multi-level thresholding problem on satellite images [11]. In [5], researchers used two meta-heuristic optimization algorithms social spiders optimization (*SSO*) and flower pollination (*FP*) to solve the segmentation problem via multi-level thresholding. A new meta-heuristic method, named tree-seed algorithm (*TSA*), wasused for multi-level thresholding with real images [12]. A new approach based on fire-fly algorithm wasproposed to find optimal thresholds for multi-level threshold problem [13].

In this study, we evaluated the performance of the *PSO* and *CSO*swarm optimization algorithms on multi-level thresholding problem withfive realimages which are taken from [14].In the experiments, PSNR[15] and the fitness function values are used as the performance criteria. The remainder of this work is organized as follows: In section II, thresholding problem is defined and reviewed. In section III, the swarm optimization algorithms used in this work are explained. In section IV, the experimental results are presented. In section V, experimental results are analyzed as conclusion.

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II. THRESHOLDING PROBLEM

Thresholding is a widely usedand simple method among the all existing segmentation techniques. Thresholding methods perform based on gray scale histogram of images. Generally, thresholding techniques can be classified into two approaches named as parametric and nonparametric approaches. In the parametric approaches, each group of gray scale range is supposed to accord to a Gaussian distribution.Then, the approaches work to find best parameters of Gaussian distribution to fit the histogram. On the other side, based on some criteria, nonparametric approaches attempt to find the threshold values that separate image into similar regions[9, 16].

There are two types of image thresholding techniques: bi-level and multi-level thresholding.Bi-level thresholding techniques use one threshold value to separate image into two classes. In these techniques, a binary image is generated from gray scale image by changing the pixel values under threshold to zero and others to one[17]. Assume that there is L ($0 < L < 255$) gray level image to be segmented. For bi-level thresholding, T is the threshold value that separate gray scale image into two classes which is calculated according to the objective function[18].

For multi-level thresholdingtechniques,number of the threshold value is greater than one and an output image has multiple groups which is generated according to equation (1). In equation (1), $I$is input image, m is the number of thresholds and $t_i$is the ith threshold value where$i$=1... m[17].

$$\begin{aligned} M_0 &= \{g(x,y) \in I | 0 \le g(x,y) \le t_1 - 1\} \\ M_1 &= \{g(x,y) \in I | t_1 \le g(x,y) \le t_2 - 1\} \\ M_{\mathrm{i}} &= \{g(x,y) \in I | t_{\mathrm{i}} \le g(x,y) \le t_{\mathrm{i+1}} - 1\} \\ M_{\mathrm{m}} &= \{g(x,y) \in I | t_{\mathrm{m}} \le g(x,y) \le L - 1\} \end{aligned} \quad (1)$$

Otsu's method is a simple and popular technique to find best threshold values. This method chooses the optimal threshold values with minimizing the within class variance or maximizing the between class variance. Also,this method can be used for both bi-level and multi-level thresholding. Assume that an input image to be divided into $\boldsymbol{M}(C_1, C_2 \ldots C_M)$groups by $\boldsymbol{M\text{-}1}(t_1, t_2 \ldots t_{M-1})$ thresholds.The main purpose of the within class variance approach is to minimizethe equation given in (2) [19].

$$\sigma_w^2 = \sum_{j=1}^{M} w_j \sigma_j^2 \quad (2)$$

where,$w_j$is the gray level distribution for the jth class and σ_j^2 is the variance of the$j$th class given by (3) and (5) respectively. Equation (4) gives the probability of gray level i, where $n_i$is the number of pixels at gray level i and N is the total number of pixels in input image.

$$w_j = \sum_{i=t_{j-1}+1}^{t_j} P_i \quad (3)$$

$$P_i = \frac{n_i}{N} \quad (4)$$

$$\sigma_j^2 = \sum_{i=t_{j-1}+1}^{t_j} (i - u_j)^2 \, P_i / w_j \quad (5)$$

$u_j$is the mean of the jth class and calculated by (6) given below:

$$u_j = \sum_{i=t_{j-1}+1}^{t_j} i \; P_i / w_j \quad (6)$$

In this paper, within class variance of Otsu's method is used as an objective function.

III. SWARM OPTIMIZATION ALGORITHMS

In this paper, the performances of two swarm optimization algorithms are evaluatedon multi-level thresholding. *PSO* and *CSO* algorithms attempted to find optimal threshold values to minimize the sum within class variance of the groups which are separated by thresholds.

A. Particle Swarm Optimization (PSO)

The PSO algorithm based on social behavior of fish or bird swarm which is proposed by Eberhart and Kennedy in 1995[20]. In the*PSO*, each particle of the swarm represents a solution with position and velocity and updatesits position to find best solution in the search space by using its best solution and the global best solution of the swarm. In the first step of the PSO,the particles are initialized at random positions by using equation (7). After the initializing process, each particle updates its position (x_i) and velocity (v_i) iteratively by using equations (8) and (9), respectively. Assume that SS is the population size and D is the dimension of the problem[21-23].

$$x_{ij} = x_j^{min} + rand(0,1)(x_j^{max} - x_j^{min}) \quad (7)$$

where,i=1 ... $SS$and j=1 ... D,$x_i$is the position of the ith particle.

$$x_{ij} = x_{ij} + v_{ij} \quad (8)$$

$$v_{ij} = w v_{ij} + c_1 r_1 (pb_{ij} - x_{ij}) + c_2 r_2 (gb_{ij} - x_{ij}) \quad (9)$$

where,x_{ij} and $v_{ij}$are the position and the velocity of the jth dimension of the ith particle, respectively. $w$is the inertia weight to balance effect of global and local search, $c_1$and c_2 are the momentum factors to affect the moving step, $r_1$and r_2 are the random numbers between 0 and 1, pb_i is the best position visited by ith particle and gb_i is the best position of the population. The pseudo code of the *PSO* algorithm is given by Fig. 1.

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```
1  Randomly initialize the population
2  Repeat
3  Calculate the fitness values of each particle
4  Find the best experience of the particles
5      Assign the best (global best) particle
6  Calculate velocity of the all particles
7  Update position of the all particles
8  Untilending criteria
```

Figure 1. Pseudo code of the PSO[23]

B. Cat Swarm Optimization (Cso)

CSO [24] is a new swarm intelligence algorithm for the optimization problems. The *CSO* algorithm is modeled based on biological behaviors of the cat swarm. In *CSO*, each cat of the population represents a solution in search space and has position, fitness value, velocity and state. CSA has two states as "*seeking mode*" and "*tracing mode*" and each cat has to be assigned into one of them. After initializing of the cat population, each cat is assigned into one moderandomly. A mixture ratio (*MR*)is defined to show the rate of seeking and tracing mode andaccording to thesemodes; each cat iteratively updates its position to find best solution in the search space. Updating of position is different in both modes[25, 26].

1) Seeking Mode: This mode is modeled to describe and present the behaviors of the cats while in resting time. In this mode, cat is looking around the envirenmont to decide about its next move. There are four important factors for a cat in this mode: seeking memory pool (SMP), seeking range of the selected dimension (SRD), counts of dimension to change (CDC) and self position consideration (SPC). The steps of the seeking mode is given below[25]:

Step 1: Create *j* copy of the current cat. If *SPC* value is true then *j=(SMP-1)* else *j=SMP*and the current position of the cat is a candidate solution.

Step 2: According to *CDC*, for each created copy, randomly minus or plus *SRD* percent the current values with replacing old ones

Step 3: Calculate the fitness value (*FS*) of each candidate cats.

Step 4: Calculate the selecting probability for all candidates by equation (10). In case of all *FS*sare equal, set all selecting probabilities as 1.

Step 5: According to selecting probabilities, move the current cat to a position among the candidates.

$$P_i = \frac{|FS_i - FS_b|}{FS_{max} - FS_{min}} \quad (10)$$

where,*i=1… j,* if the aim is to minimize the problem then $FS_b=FS_{max}$,otherwise $FS_b=FS_{min}$.

2) Tracing Mode: In this mode, each cat in tracing mode moves to the target with using its velocity.The steps of the tracing mode is given below [25, 26]:

Step 1: The velocity of the each cat is updatedaccording to the equation (11).

Step 2: Set the velocities, which over range, to the limits.

Step 3: Update the position of the *i*th cat according to the equation (12).

$$v_i = v_i + c_1 r_1 (xb_i - x_i) \quad (11)$$

$$x_i = x_i + v_i \quad (12)$$

where,c_1 is the acceleration factor to affect the velocity of the cat in searching space, $r_1$is a random number between 0 and 1 and *xb* is the position of the best cat in population.

The steps of the CSO algorithm isgivenin Fig.2[25].

```
1  Create N cats with random positions and velocities.
2  According to MR, set the mode of the each cat randomly.
3  Repeat
4      Calculate the fitness values of each cat.
5      Find the best fitness of the population and keep it.
6  According to its mode, update position of the each cat.
7  According to MR, re-set the mode of the each cat randomly
8  Until ending criteria
```

Figure 2. The main steps of the CSO algorithm

IV. EXPERIMENTAL RESULTS

PSO and CSO algorithms areimplemented on multi-level thresholding for image segmentation by using images given with grey level histogram in Fig. 3. The used parameters of the PSO algorithm are: iteration number = 200, population size (*SS*) = 100, inertia weight (*w*) = 0.6, personal learning coefficient (c_1) = 2 and global learning coefficient (c_1) = 2. The used parameters of the CSO algorithm are: iteration number = 200, population size (*N*) = 100, mixture ratio (*MR*) = 10%, seeking memory pool (*SMP*) = 5, seeking range of the selected dimension (*SRD*) = 20%, counts of dimension to change (*CDC*) = 80% and the acceleration factor (c_1) = 2.

The experimental results of the PSO and CSO algorithms aregivenin Table 1 that includes optimal threshold, PSNR and fitness function values. The within class variance is used as the fitness function and the algorithms are performed to minimize the value of the fitness function for finding the optimal threshold values. Firstly, the test images are segmented according to optimal threshold values found by the algorithmsand then*PSNR* value is calculated to measure the quality between the original (input) images and segmented (output) images. Fig. 4 shows a sample (1.gif)segmented image by algorithms with different threshold numbers.The results show that the performance of the *PSO*algorithm is better than the performance of the *CSO* algorithmfor multi-level thresholding. However, the *CSO* algorithm can also be used to solve multi-level thresholding problem due to its close performance to the *PSO*.

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V. CONCLUSION

In this paper, we used two swarm algorithms (PSO and CSO) to solve the multi-level thresholding problem for image segmentation.In the experiments, five real images are used. The algorithms attempted to find the optimal threshold values by minimizing the within class variance of the groups separated by threshold values. The experimental results show that the PSO yields better performance than the CSO. For further works, a pre-processing can be performed for test images before segmentation and/or some modified/hybrid methods can be developed.

Table I: The experimental results of the swarm optimization algorithms for multi-level thresholding

Images	#T	Threshold Values		PSNR		FS	
		PSO	*CSO*	*PSO*	*CSO*	*PSO*	*CSO*
1.gif	2	82 147	82 147	18.86	18.86	373.38	373.38
	3	75 127 176	76 130 177	25.19	25.18	196.83	197.44
	4	66 106 142 182	70 110 145 180	27.14	27.07	125.73	127.62
	5	57 88 118 148 184	52 79 116 141 184	28.54	28.25	91.02	97.22
2.gif	2	94 161	94 161	22.64	22.64	353.76	353.76
	3	83 126 179	82 126 177	25.06	25.05	202.9	203.28
	4	69 102 138 186	71 108 140 189	27.06	26.97	127.89	130.49
	5	63 91 117 147 191	68 90 119 154 191	28.49	28.24	92.11	97.42
3.gif	2	51 106	51 108	23.1	23.1	318.47	318.47
	3	50 97 172	50 96 172	25.02	25.02	204.78	204.82
	4	36 70 107 178	32 68 104 175	27.74	27.62	109.41	112.35
	5	26 52 74 106 177	21 50 70 106 187	29.46	29.23	73.51	77.54
4.gif	2	56 93	56 93	26.82	26.82	135.03	135.03
	3	53 84 111	54 85 110	28.93	28.93	83.15	83.25
	4	44 70 90 113	44 73 92 119	31.15	30.85	49.81	53.43
	5	45 70 90 110 131	44 60 74 89 115	32.18	32.05	39.3	40.46
5.gif	2	67 132	67 128	23.24	23.24	308.47	308.47
	3	59 99 139	53 98 142	25.92	25.92	166.43	166.43
	4	58 95 124 159	57 97 123 156	27.73	27.73	109.56	109.56
	5	43 66 97 123 158	44 70 105 132 160	29.87	29.87	67.01	67.01

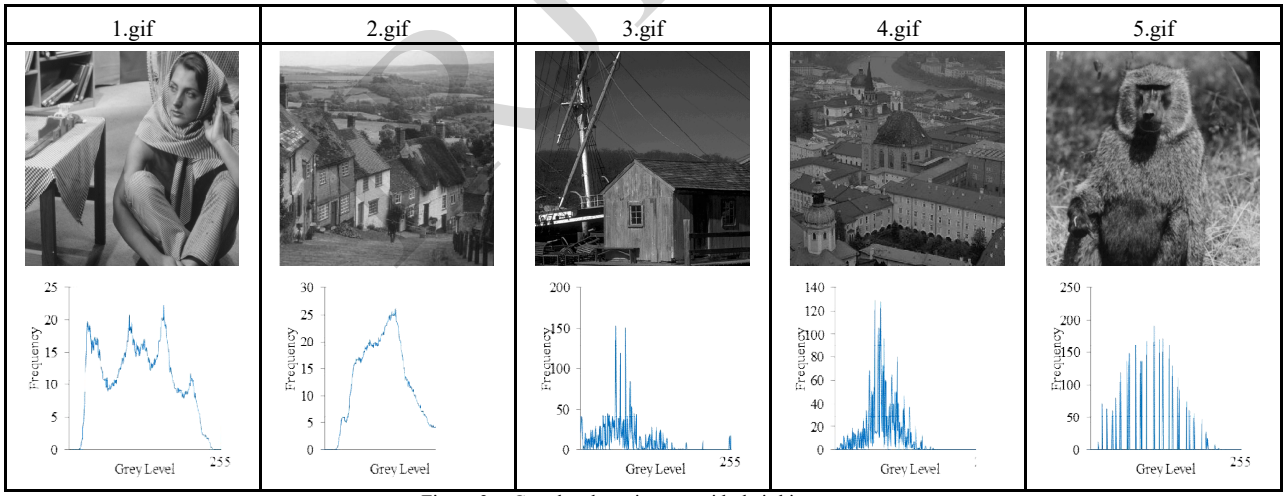


Figure 3. Grey level test images with their histogram.

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Figure 4. The segmented results for 1.gif by algorithms.

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