www.ijecs.in
International Journal Of Engineering And Computer Science ISSN: 2319-7242
Volume 5 Issue 5 May 2016, Page No. 16453-16457

Improved PSO algorithm approach in Gray scale image multi-level thresholding

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Abstract: ***The heuristic algorithm based segmentation procedures are widely used to find optimal thresholds for RGB and Gray scale images. In this paper, Otsu based bi-level and multi-level image segmentation is carried for a class of gray scaled images using Improved Particle Swarm Optimization (IPSO). Optimal thresholds for the test image are attained by maximizing Otsu's between-class variance function. The performance of the proposed IPSO based segmentation procedure is validated with the existing methods, such as Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization (BFO) algorithms. The performance assessment between algorithms are verified using well known image parameters such as objective function, Peak to Signal Ratio (PSNR), and the Structural Similarity Index Matrix (SSIM). The result shows that for most of the images, IPSO based method offers enhanced result compared to the alternatives.***

Keywords: Gray scale image, Otsu, heuristic algorithm, PSNR, SSIM.

I. INTRODUCTION

Image segmentation is widely used to examine grey scale and colour images in medical discipline, navigation, environment modelling, automatic event detection, surveillance, pattern recognition, and damage detection. The improvement in digital imaging procedure and computing technology has enlarged the potential of imaging science [1-4].

In recent years, a number of segmentation procedures are proposed to segment the gray scale images [5,6,8-10]. In this paper, histogram based image segmentation is proposed using the Otsu's between class variance function [7].

In this paper, Otsu's function directed, heuristic algorithm based bi-level and multi-level segmentation approach is considered to segment the standard test images for m = 2,3,4,5. The proposed work is demonstrated by considering four gray scale (512 x 512) images existing in the literature.

The remaining part of this paper is organized as follows: Section 2 outlines the Otsu based methodology, section 3 presents the overview of algorithms considered in this study. The results and discussion of this work is presented in section 4 and section 5 presents the conclusion.

II. OTSU

Otsu is one of the most common and widely considered image segmentation techniques [7]. This method offers the best possible thresholds by maximizing the between class variance function. This procedure is defined as follows [9-11]:

For a given RGB image, let there is L intensity levels in the range {0,1,2,…, L-1}. Then, the probability distribution P_i^C can be defined as:

$$p_i^C = \frac{h_i^C}{N} \sum_{i=0}^{L-1} p_i^C = 1 \tag{1}$$

where i =specific intensity level in the range $\{0 \le i \le L-1\}$, C = {R,G,B}, N = total number of pixels in the image, and h_i^C = number of pixels for the corresponding intensity level I in component C.

The total mean of each component is calculated as:

$$\mu_T^C = \sum_{i=0}^{L-1} i p_i^C = 1 \tag{2}$$

The m - level thresholding presents m-1 threshold levels t_j^c, where j = 1,2,…,m-1, and the operation is performed as:

$$F^C(x,y) = \begin{cases} 0, & f^C(x,y) \le t_1^C \\ \frac{1}{2}(t_1^C + t_2^C), & t_1^C < f^C(x,y) \le t_2^C \\ \vdots & \vdots \\ \frac{1}{2}(t_{m-2}^C + t_{m-1}^C), & t_{m-2}^C < f^C(x,y) \le t_{m-1}^C \\ L-1, & f^C(x,y) > t_{m-1}^C \end{cases} \tag{3}$$

where in x and y are the width (W) and height (H) of the pixel of the image of size H × W denoted by $f^C(x, y)$ with L intensity levels for each component.

The probabilities of occurrence w_j^C of classes $D_i^C,\ldots,D_m^C$ are given by:

$$w_j^C = \begin{cases} \sum p_i^C, & j = 1 \\ \sum +1 p_i^C, & 1 < j < m \\ \sum +1 p_i^C, & j = m \end{cases} \tag{4}$$

$$\mu_j^C = \begin{cases} \sum \frac{p_i^C}{w_j^C q}, & j = 1 \\ \sum +1 \frac{p_i^C}{w_j^C}, & 1 < j < m \\ \sum +1 \frac{p_i^C}{w_j^C}, & j = m \end{cases} \tag{5}$$

$$\sigma_B^{C^2} = \sum_{j=1}^{m} w_j^C \left(\mu_j^C - \mu_T^C\right)^2 \tag{6}$$

where w_j^C= probability of occurrence, and μ_j^C = mean.

Finally, the m – level thresholding is reduced to an optimization problem to search for t_j^C, that maximize the objective function of each image component C can be defined as:

$$\phi^C = \max_{1 < t_i^C < \cdots, L-1} \sigma_B^{C^2}(t_j^C) \tag{7}$$

Along with the above cost function value, the well known image quality measures, such as the Peak Signal-to-

DOI: 10.18535/ijecs/v5i5.20

Noise Ratio (PSNR) and Structural Similarity Index Matrix (SSIM) are also considered and its mathematical expression is given below: $\mathrm{PSNR}_{(x,y)} = 20\log_{10}\left(\frac{255}{\sqrt{\mathrm{MSE}_{(x,y)}}}\right)$; dB (8)

$$\mathrm{SSIM}_{(x,y)} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_{x^2} + \mu_{y^2} - C_1)(\sigma_{x^2} + \sigma_{y^2} + C_2)} \quad (9)$$

where x and y are original and segmented images; μ_x and μ_y are the average values, σ_x^2 and σ_y^2 are the variance, σ_{xy} is the covariance, and $C_1 = (k_1L)^2$ and $C_2 = (k_1L)^2$ stabilize the division with weak denominator, with L = 256, k_1 = 0.01, and k_2 = 0.03 [9-11].

III. Heuristic Algorithms

In the past decades, heuristic algorithms are emerged as a powerful tool in solving a class of constrained and unconstrained optimization tasks. In the proposed work, the image segmentation is carried using some well-known heuristic algorithms, such as PSO, BFO and IPSO algorithms.

a. Particle Swarm Optimization

Traditional PSO was developed by the motivation of the social behavior in flock of birds and school of fish [12, 16]. It has two basic equations, such as the velocity update and position update as presented below:

$$V_i(t+1) = W^t.V_i^t + C_1R_1(P_i^t - S_i^t) + C_2R_2(G_i^t - S_i^t) \quad (10)$$

$$X_i(t+1) = X_i^t + V_i(t+ \quad (11)$$

where = inertia weight coefficient (typically 0.8), = current velocity of particle, $V_i(t+$= updated velocity of particle, = current position of particle, $X_i(t+$= updated position of particle, *R1* and *R2* are random numbers between {0,1}, *C1* = cognitive coefficient (typically 2.0), and *C2* = social coefficient (typically 1.58).

b. Bacterial Foraging Optimization

BFO is developed by mimicking the foraging activities of *E. coli* bacteria. In this work, the enhanced BFO algorithm proposed by Rajinikanth and Latha have been adopted [13].

The initial algorithm parameters are assigned as follows [17-20]:

Numberof *E.Coli* bacteria = N

$N_c = \frac{N}{2}$; $N_s = N_{re}\frac{N}{3}$; $N_{ed}\frac{N}{4}$; $N_r = \frac{N}{2}$; Ped = $\left(\frac{N_{ed}}{N+N_r}\right)$; $d_{attractant}$ = $W_{attractant} = \frac{N_s}{N}$; and $h_{repellant} = W_{repellent} = \frac{N_c}{N}$. (12)

c. Improved PSO algorithm

The Improved PSO was initially proposed by Chang and Shih [14]. In this work, they modified the velocity update equation as presented below:

$$V_i^{(t+1)} = W^t.V_i^t + C_1R_1(\mathrm{pbest} - S_i^t) + C_2R_2(\mathrm{gbest} - S_i^t) + C_3R_3(\mathrm{ibest} - S_i^t)$$

Compared with the traditional PSO, it has additional parameters, such as C_3 and R_3. The position update is similar to the traditional PSO algorithm as presented in eqn. 11 [15].

d. Implementation

In the proposed work, the Otsu guided heuristic algorithms continuously investigates the histogram of the test image until the objective function is maximized (eqn. 7). Maximization of Otsu's between-class variance function is chosen as the objective function (J_{max}).

The initial algorithm parameters are assigned as follows: number of agents= 20, number of iterations = 500, stopping criteria = J_{max}. For each image and for the chosen 'm' value, the segmentation operation is repeated ten times and the mean of the trial is chosen as the optimized result.

IV. Result and Discussions

Otsu guided, heuristic algorithm based multi-level thresholding have been tested on four standard test images such as Hunter, Jet, Road, Butterfly, House and Map image. All the test images are 512 x 512 sized gray scale images. In the test images, most of them are difficult to segment because of its multimodal histograms.

The segmentation experiment was performed on a work station with an Intel Dual Core 1 GHz CPU with 1.5GB of RAM and equipped with MATLAB R2012 software.
During the simulation work, each image is examined with a number of thresholds such as m = 2 to 5. The simulation study is repeated 10 times individually and the mean value among the search is recorded as the optimal threshold value.

Initially, the thresholding method is applied on the Hunter image. Table 1 depicts the considered image dataset, the gray scale histograms and segmented images with IPSO algorithm. This image segmentation process is repeated 10 times for each 'm' and the mean value is chosen as the optimized result.

The performance measure values of the proposed research work are presented in Table 2 and Table 3 for the considered gray scale image dataset.

Table 2 presents the maximized objective function value (J_{max}) the corresponding optimal threshold values for m = {2,3,4,5}. Table 3 shows the PSNR value, SSIM and the number of iterations taken by the heuristic algorithms considered in this study.

From these results, it is clear that, the considered IPSO algorithm offers better result in J_{max}, PSNR and SSIM compared with the traditional PSO and BFO algorithms. From Table 3, it can be observed that, the number of iteration taken by the IPSO algorithm is small compared with the PSO and BFO.

Hence, the IPSO algorithm can be used to segment the standard test images existing in the literature.

Table 1. Original and segmented test images

	Original Image	Histogram	m = 2	m = 3

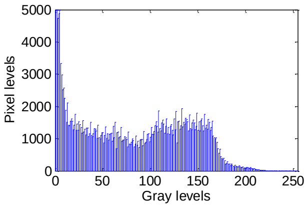
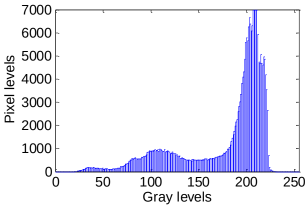
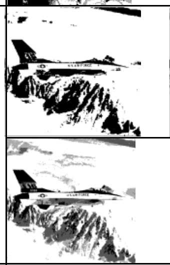
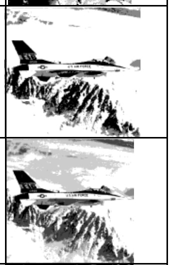
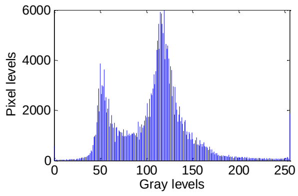
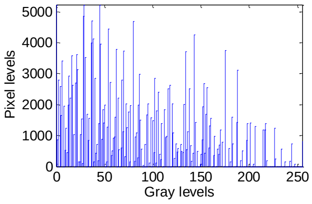
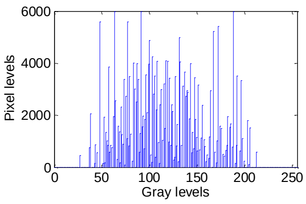
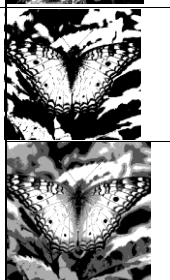
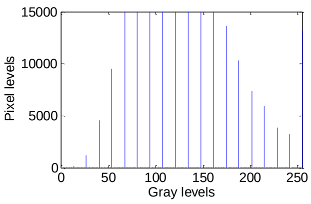
			m = 4	**m = 5**
Hunter				
Jet				
Road				
House				
Butterfly				
Map				

Table 2. Objective function and the corresponding threshold values

DOI: 10.18535/ijecs/v5i5.20

	m	Objective function			Optimal thresholds		
		IPSO	BFO	PSO	IPSO	BFO	PSO
Hunter	2	2741.61	2739.50	2738.11	48, 133	50, 137	50, 134
	3	2972.04	2955.27	2970.35	34,95,146	30,92,148	32,96,150
	4	3101.22	3100.91	3099.82	24,81,112,154	21,82,114,153	20,80,116,155
	5	3203.04	3203.11	3201.68	18,66,92,117,163	20,62,90,120,166	18,64,95,118,162
Jet	2	1802.41	1800.94	1798.84	110, 171	110, 170	110, 170
	3	1869.35	1858.27	1768.10	90, 148, 199	88, 145, 196	90, 146, 192
	4	1954.73	1934.55	1955.00	81, 127, 170, 212	80, 124, 172, 206	80, 124, 168, 214
	5	1979.61	1977.81	1976.99	66,102,140,185,221	68,90,138,184,218	67,100,140,186,220
Road	2	1368.22	1369.17	1366.05	82, 162	86, 160	82, 164
	3	1418.37	1413.09	1413.81	74, 124, 191	72, 128, 190	74, 128, 194
	4	1488.51	1490.25	1487.16	66, 104, 134, 203	66, 108, 138, 200	62, 111, 139, 197
	5	1500.21	1497.74	1499.55	64,98,128,168,212	61,92,132,162,210	60,97,126,171,208
House	2	2962.04	2960.73	2961.18	88,172	86,170	88,174
	3	3075.48	3011.35	3038.10	76, 110, 179	74, 111, 181	74, 114, 179
	4	3103.55	3099.13	3101.84	70, 96, 142, 188	68, 98, 141, 186	67, 94, 140, 182
	5	3141.75	3128.94	3138.99	64,102,148,176,191	63,79,144,171,194	60,102,145,176,192
Butterfly	2	1651.13	1650.36	1651.03	94,166	93,168	94,168
	3	1773.45	1771.27	1770.92	86, 122, 171	84, 120, 173	84, 123, 174
	4	1802.04	1802.00	1801.78	69, 110, 138, 178	67, 111, 137, 180	72, 114, 141, 180
	5	1817.22	1816.80	1816.36	64,98,120,165,181	61,91,126,170,184	62,99,126,160,185
Map	2	2371.44	2370.71	2371.02	112, 178	112, 179	111, 176
	3	2570.03	2571.30	2568.81	95, 142, 198	94, 140, 192	92, 144, 201
	4	2614.92	2613.15	2613.60	86, 120, 171, 222	81, 124, 170, 220	84, 122, 175, 216
	5	2688.01	2686.88	2687.47	74,122,141,183,226	71,89,142,185,221	70,126,139,186,223

Table 3. Performance measure values obtained with heuristic algorithms

	m	SSIM			CPU time (min)		
		IPSO	BFO	PSO	IPSO	BFO	PSO
Hunter	2	0.7358	0.7330	0.7347	0.4206	0.4371	0.4392
	3	0.8004	0.8031	0.8028	0.5311	0.5420	0.5494
	4	0.8073	0.8052	0.8060	0.6609	0.6193	0.6835
	5	0.8105	0.8091	0.8083	0.7031	0.6735	0.7101
Jet	2	0.6976	0.7027	0.7004	0.3947	0.3852	0.3985
	3	0.7198	0.7201	0.7141	0.6342	0.6648	0.6831
	4	0.7502	0.7488	0.7492	0.8056	0.8142	0.8173
	5	0.7944	0.7903	0.7932	0.9351	0.9701	0.9582
Road	2	0.6936	0.7002	0.7009	0.6329	0.7920	0.7634
	3	0.7287	0.7106	0.7215	0.7931	0.8437	0.8501
	4	0.7519	0.7482	0.7501	0.9326	0.9455	0.9513
	5	0.7936	0.7819	0.7823	0.9773	0.9679	0.9915
House	2	0.7065	0.7093	0.6984	0.7437	0.7525	0.7593
	3	0.7191	0.7187	0.7166	0.8036	0.8102	0.8163
	4	0.7512	0.7482	0.7500	0.8287	0.8306	0.8313
	5	0.7825	0.7805	0.7837	0.9239	0.9480	0.9522
Butterfly	2	0.7197	0.7054	0.7132	0.5399	0.5471	0.5492
	3	0.7561	0.7502	0.7527	0.6492	0.6731	0.6638
	4	0.7918	0.7893	0.7882	0.7355	0.7826	0.7604
	5	0.8103	0.8036	0.8075	0.9302	0.9471	0.9522
Map	2	0.7329	0.7284	0.7291	0.6340	0.6832	0.6703
	3	0.7503	0.7469	0.7481	0.8361	0.8871	0.8709
	4	0.7773	0.7779	0.7743	0.9033	0.9408	0.9472
	5	0.8115	0.8037	0.8095	0.9882	0.9792	0.9904

V. CONCLUSION

In this paper, gray level histogram assisted image thresholding problem is addressed using IPSO, PSO and BFO algorithms. The simulation study is carried using Matlab software. Maximization of Otsu's between class variance function is chosen as the objective function. The performance of the proposed segmentation procedure is evaluated using PSNR, SSIM and the number of iteration for the algorithm convergence. From this study it is noted that, from m = 2 and3 the number of iteration taken by the heuristic algorithm is small. The result also confirms that, for m > 3, IPSO algorithm provides better results in objective function, PSNR, SSIM and number of iterations compared with PSO and BFO algorithms.

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