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Optimal Multi-level Image Segmentation using Bounded Heuristic Search Technique

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ABSTRACT

Image thresholding is widely considered to obtain binary image from the gray level image. In this article, histogram based multi-level thresholding approach is proposed using Brownian Distribution (BD) based Bat Algorithm (BA). The optimal thresholds for the gray scale images are attained by maximizing Otsu's between class variance function. The performance of the proposed algorithm is demonstrated by considering six benchmark (512 x 512) images and compared with the existing algorithms such as improved Particle Swarm Optimization (PSO), enhanced Bacterial Foraging Optimization (BFO) and Levy flight Bat Algorithm (LBA). The performance assessment between algorithms is carried out using the parameters such as objective function, Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and convergence of algorithms. The result evident, even though the convergence time is large, that BD guided BA provides better performance measure values for most of the images compared with the PSO, BFO and LBA algorithms considered in this study.

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INTRODUCTION

Image processing a vital procedure used to analyze the gray scale and color images in various fields. Image thresholding is one of the well known image preprocessing techniques used to adjust the features of an image. For gray scale images, bi-level and multi-level thresholding procedure is used to highlight the key features from the raw image. The main motive of the thresholding procedure is to enhance the key feature of an image using the best possible threshold level.

In the image processing field, finding the exact threshold value to separate the available image into desirable object and background remains an extremely a challenging task. In the literature, a number of methods are proposed to segment the test images (Lee *et al*., 1990; Pal and Pal, 1993; Sezgin and Sankar, 2004; Hammouche *et al*., 2010; Tuba, 2014). Methods such as Tsallis, Kapur, Kittler, Otsu, Li-Lee, Pun, Renyi, etc. are widely adopted by most of the researchers to segment the gray scale images (Mello and Schuler, 2008). Among them, Otsu's method is widely adopted by most of the researchers for gray scale and color image segmentation, because of its simplicity, ease of implementation and high accuracy (Akay, 2013; Ghamisi *et al*., 2010; 2012; 2013).

During the multi-level thresholding technique, finding the optimal threshold using traditional method is very difficult and time consuming. Hence, in recent years, heuristic algorithm based optimal thresholding approaches are widely adopted by most of the researchers. Heuristic algorithm based approaches, such as Particle Swarm Optimization (Sathya and Kayalvizhi, 2010; Raja *et al*., 2012; Rajinikanth *et al*., 2014), Bacterial Foraging Optimization (Sathya and Kayalvizhi, 2011), Firefly Algorithm (Raja *et al*., 2014) and Bat Algorithm (Rajinikanth *et al*., 2014; Subadhra *et al*., 2014) are widely considered to solve bi-level and multi-level thresholding problem for a class of gray scale images.

In the proposed work, Otsu's between-class variance function based bi-level and multi-level image thresholding is implemented using improved PSO, enhanced BFO and LBA algorithms existing in the literature. The optimization accuracy of the traditional bat algorithm is improved using the Brownian Distribution strategy discussed in the paper by Raja *et al.* (2014). In order to evaluate the performance of the considered algorithms and the BBA, 512 x 512 sized six standard gray scale test images, such as Living room, Bee, Crane, Boat house, Palace and Park are considered. The performance of the segmentation technique is assessed using the image

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parameters, such as J_{max}, PSNR and SSIM. The convergence of the heuristic search always depends on the agents (population), dimension of search (number of parameters to be optimized) and the boundary of search universe.

In order to minimize the convergence time and to maximize the optimization accuracy, most of the researchers followed a bounded heuristic search in variety of engineering optimization problems. In this paper, the bounded threshold search technique recently discussed by Raja *et al*. (2014) is adopted to enhance the outcome of the multi-level thresholding problem. Concept wise it is similar to the fast Otsu segmentation procedure discussed by Liao *et al*. (2001). From this study it is noted that, the bounded search technique helps to achieve better result for all the considered image data set for m = 2,3,4,5. The PSO and LBA helps to achieve better convergence rate where as the BBA offers better J_{max}, PSNR and SSIM values compared with PSO, BFO and LBA.

This paper is organized as follows: Section 2 presents the over view of Otsu. Section 3 presents the summary of the algorithms considered in this study. Experimental results are appraised and discussed in Section 4. Conclusion of the present research work is given in section 5.

OTSU:

Otsu's image thresholding procedure is originally proposed in 1979 (Otsu, 1979). In this method the bi-level and multi-level thresholds can be attained by maximizing the Otsu's between-class variance function.

A detailed explanation of Otsu's function could be found in (Akay, 2013; Ghamisi *et al*., 2010; 2012; 2013).

Bi-level thresholding:

In bi-level thresholding, the image is divided into two classes such as C_0 and C_1 by a threshold at a level 't'. The class C_0 encloses the gray levels in the range 0 to t-1 and class C_1 encloses the gray levels from t to L – 1. The probability allocation for C_0 and C_1 can be expressed as;

$$C_0 = \frac{p_0}{\omega_0(t)} \cdots \frac{p_{t-1}}{\omega_0(t)} \quad \text{and} \quad C_1 = \frac{p_t}{\omega_1(t)} \cdots \frac{p_{L-1}}{\omega 1(t)} \tag{1}$$

where $\omega_0(t) = \sum_{i=0}^{t-1} p_i$, and $\omega_1(t) = \sum_{i=t}^{L-1} p_i$

The mean levels μ_0 and μ_1 for C_0 and C_1 can be written as;

$$\mu_0 = \sum_{i=0}^{t-1} \frac{ip_i}{\omega_0(t)} \quad \text{and} \quad \mu_1 = \sum_{i=t}^{L-1} \frac{ip_i}{\omega 1(t)} \tag{2}$$

The mean intensity (μ_t)of the entire image can be represented as;

$\mu_T = \omega_0\mu_0 + \omega_1\mu_1$ and $\omega_0 + \omega_1 = 1$

The objective function for the bi-level thresholding problem can be expressed as;

$$J_{max} = \sigma_0 + \sigma_1 \tag{3}$$

Multi-level thresholding:

In multi-level thresholding , let us consider *'m'* thresholds (t_1, t_2, …, t_m), which split the image into *'m'* classes: C_0 with gray levels in the range 0 to t-1, C_1 with enclosed gray levels in the range t_1 to t_2-1, …, and C_m includes gray levels from t_m to L – 1. The objective function for this problem can be expressed as;

$$J_{max} = \sigma_0 + \sigma_1 + \ldots + \sigma_m \tag{4}$$

where $\sigma_0=\omega_0(\mu_0-\mu_t)^2$,$\sigma_1=\omega_1(\mu_1-\mu_t)^2$, … , $\sigma_m=\omega_m(\mu_m-\mu_t)^2$.

* in this work, objective functions are assigned for m=2, m=3, m=4, and m=5.

Performance measures:

The image quality measures, such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Matrix (SSIM) are considered to evaluate the quality of the segmented image.

The mathematical expression is given below:

$$PSNR_{(x,y)} = 20 \log_{10}\left(\frac{255}{\sqrt{MSE_{(x,y)}}}\right); \text{dB} \tag{5}$$

$$SSIM_{(x,y)} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 - C_1)(\sigma_{x^2} + \sigma_{y^2} + C_2)} \tag{6}$$

Overview of heuristic algorithms in this study:

In literature, a considerable number of heuristic algorithms are available (Yang, 2008). In this paper, following heuristic algorithms are considered to solve the bi-level and multi-level thresholding problem:

Improved Particle Swarm Optimization:

Traditional PSO was proposed by Kennedy and Eberhart (1995). This algorithm has two basic mathematical relations such as velocity update (eqn.7) and position update (eqn.8).

$$V_i(t+1) = W^t.V_i^t + C_1R_1(P_i^t - S_i^t) + C_2R_2(G_i^t - S_i^t) \tag{7}$$

$$X_i(t+1) = X_i^t + V_i(t+1) \tag{8}$$

where W^t – inertia weight = 0.8, V_i^t - current velocity, $V_i(t+1)$ - updated velocity, X_i^t - current position, $X_i(t+1)$ - updated position, R_1, R_2 are the random values [0,1], and $C_1 = C_2 = 2.0$.

In this work, improved PSO algorithm proposed by Chang and Shih (2010) is considered. A detailed description of this algorithm can be found in (Rajinikanth and Latha, 2011). The velocity update equation available in this algorithm is presented below:

$$V_i(t+1) = W^t.V_i^t + C_1R_1(P_i^t - S_i^t) + C_2R_2(G_i^t - S_i^t) + C_3R_3(I_i^t - S_i^t) \tag{9}$$

where C_3 = 1.5, R_3 - random number in the range [0,1] and I_i^t - ibest value.

Bacterial Foraging Optimization:

Traditional BFO was proposed by Pasino by mimicking the foraging behavior of E. coli bacteria (2002). In this work, the enhanced BFO algorithm discussed in the recent image segmentation article by Rajinikanth *et al*. (2014) is adapted. The main advantage of enhanced BFO compared with the traditional BFO is, the number of initializing parameters to be assigned is less.

The initial algorithm parameters are assigned as follows;

Number of E.Coli bacteria = N ; $N_c = \frac{N}{2}$; $N_s = N_{re} \approx \frac{N}{3}$; $N_{ed} \approx \frac{N}{4}$; $N_r = \frac{N}{2}$; Ped = $\left(\frac{N_{ed}}{N+N_r}\right)$; dattractant = Wattractant = $\frac{N_s}{N}$; and hrepellant = Wrepellent = $\frac{N_c}{N}$ (10)

Bat Algorithm:

The Bat Algorithm (BA) is based on the bio-sonar characteristics of microbats. BA was proposed by modelling the navigating and tracking capability of bats (Yang, 2010). A detailed description about the BA algorithm can be found in (Yang and Gandomi, 2012; Yang, 2013; Kotteeswaran and Sivakumar, 2013; Alihodzic and Tuba, 2014).

The Traditional BA (TBA) has three mathematical discrete equations, defining the velocity update (eqn. 11), the position update (eqn. 12), and the frequency vector (eqn. 13) as given below:

$$V_i(t+1) = V_i(t) + (X_i(t) - Gbest)F_i \tag{11}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{12}$$

$$F_i = F_{min} + (F_{max} - F_{min})\beta \tag{13}$$

where β is a random integer in the range [0,1].

From eqn. 11, it is noted that, the velocity update mainly depends on the frequency vector. During the optimization search, a new solution for each bat is generated based on the following relation:

$$X_{new} = X_{old} + \varepsilon A^t \tag{14}$$

where ε is a random numeral in the range [-1,1] and A is the loudness of emitted sound by bats during the exploration of search space.

The minimum and maximum values of the loudness variable A is chosen as A_0 = 10, and A_{min} =1 (which decay in steps of 0.01). Other related mathematical representations for loudness adjustment are presented below:

$$A_i(t+1) = \alpha A_i(t) \tag{15}$$

$$r_i(t+1) = r_i(0)[1 - exp(-\gamma t)] \tag{16}$$

where α and γ are constants typically assigned with a numeral value of 0.8.

In the proposed work, we replaced 'ε' with a Brownian Distribution (BD) parameter recently discussed by Raja *et al*. (2014). A detailed explanation about the LF and BD could be found in the book by Yang (2008).

In the proposed work, the new position of the Bat can be expressed with the following relation:

$$X_{new} = X_{old} + A^t \oplus LF \tag{17}$$

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$$X_{new} = X_{old} + A^t \oplus BD \tag{18}$$

Eqn. 17 represents the position expression for LBA and eqn.18 shows the position expression for BBA. The implementation of heuristic algorithm based multi-level threshold search technique is clearly depicted in the recent articles (Raja *et al*., 2014; Rajinikanth *et al*., 2014; Subadhra *et al*., 2014)

RESULTS AND DISCUSSIONS

In this paper, the gray level histogram based bi-level and multi-level image thresholding experiment is implemented in Matlab R2012b on an Intel Core i3 2.6 GHz CPU, 4GB RAM running window 8 system.

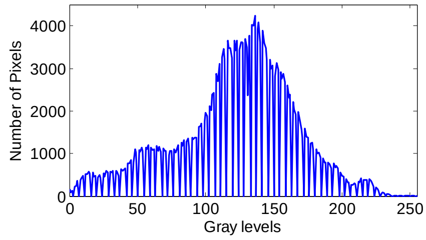
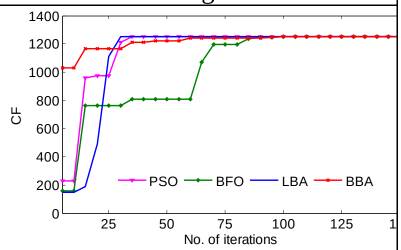
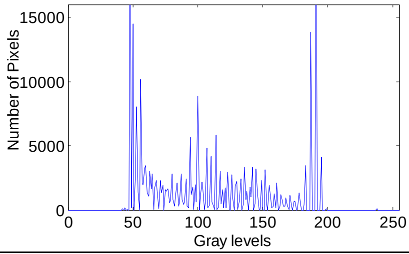
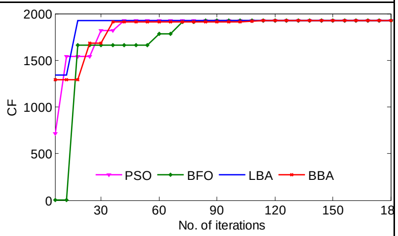
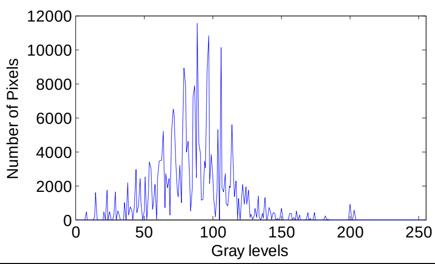
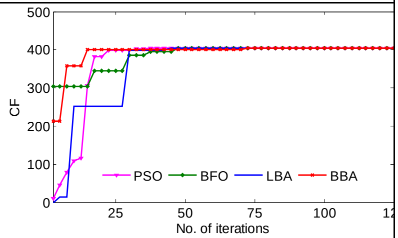
The proposed thresholding method is implemented on 512 x 512 sized six standard test images, such as Living room, Bee, Crane, Boat house, Palace and Park. From the gray level histogram, it can be observed that, these images show a multi model and oscillatory pixel levels, and hence it is quite difficult to segment these images with the conventional segmentation procedures existing in the literature.

Finding the optimal threshold in the entire threshold level [0 to L-1] is difficult and time consuming. Hence, in the proposed work, the bounded histogram based technique recently discussed by Raja *et al*. (2014) is adopted. Based on the pixel level, a boundary is assigned to limit the heuristic algorithm based exploration. The added advantage of this method is, with a minimal number of iteration, one can obtain the best possible threshold value based on the assigned '*m*' value.

In the proposed method, maximization of Otsu's between-class variance function (J_{max}) is chosen as the objective value. The heuristic algorithm based search technique, arbitrarily explores the entire search space until it finds a J_{max} value for the assigned 'm'.

Initially, the thresholding procedure is applied on the Living room, Bee and Crane images depicted in Table 1. This table also presents the corresponding histogram. For each image and for each assigned 'm' value, the thresholding procedure is repeated 20 times and the average value among the trial is chosen as the optimized result. During the optimization exploration, the search boundaries for the images are assigned as: Living room = 30 < gray level < 200, Bee = 50 < gray level < 200 and Crane = 0 < gray level < 150 as shown in Fig 1 (a) – (c).

Table 1: 512 x 512 image dataset, histogram and convergence of optimization search

<table>
<tr><th></th><th>Image</th><th>Histogram</th><th>Convergence</th></tr>
<tr><td>Living room</td><td></td><td>
</td><td>
</td></tr>
<tr><td>Bee</td><td></td><td>
</td><td>
</td></tr>
<tr><td>Crane</td><td></td><td>
</td><td>
</td></tr>
</table>

Initially, the PSO based method is applied on these images and later other heuristic algorithms, such as BFO, LBA and BBA are applied. The convergence of heuristic search for m = 2 is presented in Table 1. The BBA based segmented images for m = 2,3,4,5 are presented in Table 2 and the corresponding performance measure values are presented in Table 4 and Table 5. From Table 4 and Table 5 values, it is noted that, the improved PSO and LBA offers better convergence value compared with the enhanced BFO and BBA algorithms. But, for most of the images, the BBA algorithm offers better objective function, PSNR and SSIM values compared with the alternatives considered in this paper.

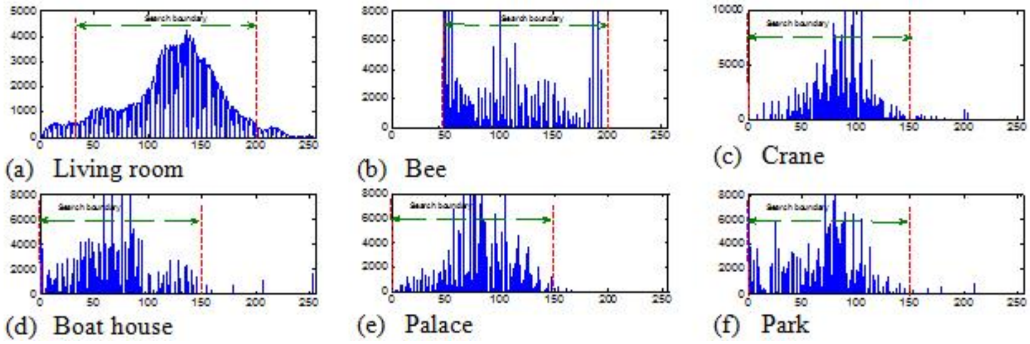
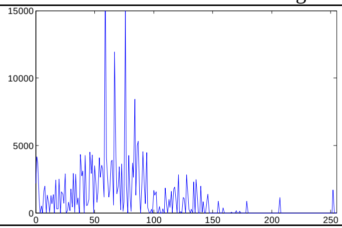
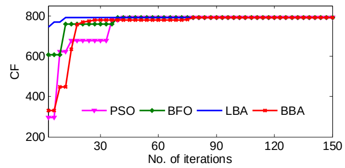
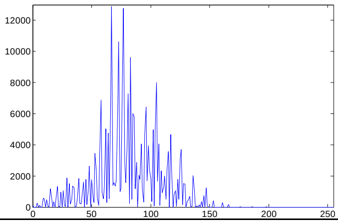
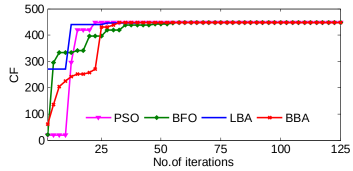


Fig 1: Search boundaries assigned for the 512 x 512 image database.

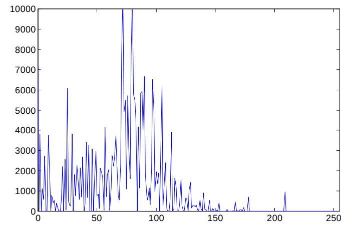
Table 2: Thresholded images with BBA.

	Multi – level thresholding for m = 2,3,4,5			
Living room	m = 2 	m = 3 	m = 4 	m = 5 
Bee	m = 2 	m = 3 	m = 4 	m = 5 
Crane	m = 2 	m = 3 	m = 4 	m = 5 

Table 3: Gray scale image dataset, histogram and convergence rate

	Image	Histogram	Convergence
Boat house			
Palace			

Park



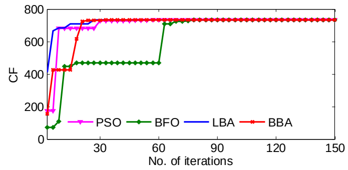


Table 4: Performance measure values with PSO, BFO, LBA and BBA.

Image	m	J_{max}				PSNR (dB)				SSIM			
		PSO	BFO	LBA	BBA	PSO	BFO	LBA	BBA	PSO	BFO	LBA	BBA
Living room	2	1246.13	1272.26	1253.20	1248.49	14.23	14.96	14.82	14.06	0.5881	0.6268	0.5904	0.6217
	3	1293.03	1295.72	1285.62	1304.64	16.19	15.98	16.88	16.81	0.6043	0.6404	0.6129	0.6496
	4	1306.11	1311.02	1298.03	1312.00	18.30	18.64	17.56	19.03	0.6257	0.6515	0.6362	0.6812
	5	1326.39	1341.85	1311.75	1325.74	19.75	20.15	20.01	20.14	0.6835	0.6911	0.6811	0.7081
Bee	2	1925.61	1955.32	1948.22	1984.17	14.20	14.95	14.52	14.88	0.5590	0.6025	0.5840	0.6180
	3	1973.20	1984.73	1967.49	1994.28	15.84	15.92	15.66	15.91	0.5826	0.6197	0.6036	0.6617
	4	1992.83	1990.36	1996.28	2002.37	16.59	17.05	16.83	16.99	0.6279	0.6516	0.6472	0.6718
	5	2061.15	2058.28	2047.19	2042.19	18.04	18.51	17.85	17.88	0.6725	0.6827	0.6900	0.6800
Crane	2	403.55	410.85	406.71	408.86	15.35	14.93	15.02	15.74	0.5947	0.6117	0.5835	0.6219
	3	451.07	447.36	441.00	461.44	16.81	16.99	16.38	17.08	0.6438	0.6735	0.6217	0.6618
	4	494.82	507.31	486.19	502.85	17.14	17.33	17.10	17.62	0.6841	0.6902	0.6783	0.7027
	5	513.95	522.85	511.65	523.01	19.32	20.16	19.11	20.89	0.7047	0.7001	0.6815	0.7081
Boat house	2	792.70	783.66	785.61	790.55	16.23	16.77	15.85	16.11	0.5519	0.5830	0.5383	0.5836
	3	812.06	815.01	794.62	811.06	18.84	17.93	17.20	18.74	0.5835	0.5992	0.5826	0.5995
	4	833.47	831.98	827.90	842.77	19.61	18.40	18.93	19.82	0.6291	0.6392	0.6029	0.6136
	5	860.25	870.03	858.27	879.00	20.05	20.32	19.66	20.85	0.6838	0.6815	0.6782	0.6824
Palace	2	447.64	471.17	452.18	469.02	15.29	16.82	16.23	16.42	0.5118	0.5338	0.5299	0.5649
	3	462.81	485.11	463.46	481.39	17.02	17.77	16.95	18.20	0.5629	0.5710	0.5512	0.5832
	4	480.66	486.05	477.21	496.42	18.11	19.13	17.39	19.52	0.5901	0.6133	0.6103	0.6300
	5	502.50	493.77	492.16	499.01	20.15	20.51	19.34	20.37	0.6219	0.6892	0.6734	0.7005
Park	2	733.56	746.30	742.19	739.38	16.10	16.81	15.73	16.15	0.6392	0.5825	0.6129	0.6389
	3	751.44	761.57	759.03	773.92	18.23	17.99	16.58	17.27	0.6519	0.6392	0.6649	0.6835
	4	780.17	794.20	777.63	786.13	19.11	18.54	18.62	19.15	0.6810	0.6772	0.6902	0.7017
	5	795.62	810.04	796.84	806.26	19.85	20.15	19.90	20.53	0.6992	0.7018	0.7038	0.7023

Table 5: Optimal thresholds and iteration number with PSO, BFO, LBA and BBA.

Image	m	Threshold values				No. of iterations			
		PSO	BFO	LBA	BBA	PSO	BFO	LBA	BBA
Living room	2	70, 152	68, 153	71, 150	70, 154	32	78	27	74
	3	59,138,182	55,134,180	56,133,181	58,135,181	92	104	83	112
	4	56,82,134,184	52,80,132,182	54,82,136,185	55,80,138,188	112	127	106	133
	5	46,77,116,153,188	48,74,112,157,185	45,75,116,152,189	46,80,114,158,192	154	177	138	202
Bee	2	98,173	101,174	102,171	98,170	57	83	26	48
	3	74,118,182	72,115,180	78,130,181	76,128,183	81	94	66	97
	4	62,86,158,187	66,82,145,183	63,88,139,182	64,82,141,184	101	133	93	151
	5	58,108,153,170,191	57,92,142,174,194	56,99,150,178,191	55,97,148,171,193	118	167	98	163
Crane	2	74,137	72,136	71,134	72,135	26	49	26	23
	3	53,106,142	51,103,140	55,107,141	56,102,140	91	109	82	127
	4	36,82,125,145	39,84,123,142	39,80,128,143	33,80,129,142	118	152	105	154
	5	18,62.94,128,147	22,60.97,133,145	19,64.91,138,147	16,68.90,125,145	163	205	139	227
Boat house	2	81,128	82,126	80,132	78,125	44	48	22	53
	3	67,113,133	64,115,136	62,118,138	61,121,135	78	101	82	117
	4	42,66,120,138	43,69,123,139	46,68,125,141	47,62,127,139	105	138	98	146
	5	29,58.98,115,144	26,55.99,118,146	32,62.94,119,148	31,53.95,118,146	117	160	116	189
Palace	2	78,114	76,111	75,115	74,116	29	54	19	34
	3	59,116,128	53,117,126	56,118,129	58,121,126	82	101	86	107
	4	46,78,124,132	43,79,128,130	40,81,128,135	41,74,127,130	115	138	106	144
	5	34,58,92,129,141	32,53,97,131,142	30,61,95,124,145	30,58,98,133,146	163	204	192	227
Park	2	66,118	68,120	69,122	62,122	41	77	30	38
	3	48,96,122	51,98,124	46,94,126	51,93,126	92	104	88	130
	4	31,66,114,128	44,67,111,132	34,62,118,131	38,65,112,135	117	138	101	159
	5	24,47,78,117,138	28,45,74,113,141	29,49,76,121,142	30,48,82,119,140	161	196	172	226

The proposed segmentation procedure is then applied on other test images, such as Boat house, Palace and Park shown in Table 3. This table also depicts the gray level histogram and the convergence of heuristic algorithm based search for 'm=2'. From the gray level histogram, it is noted that, the histogram of Boat house, Palace and Park images are similar with the histogram of the Crane. Hence for these images the search boundary is assigned as: 0 < gray level < 150 and is clearly presented in Fig 1 (d) – (f).

The considered thresholding methodology is applied on these images and corresponding results are tabulated in Table 4 and 5. From Table 4 and Table 5 values, the major observation is that, the PSO and LBA algorithm offers better convergence with relatively smaller iteration number. The BBA based technique offers better J_{max} , PSNR and SSIM for most of the cases compared with the PSO, BFO and LBA. From Table 5, it is also observed that, when 'm' level increases, due to the complexity, the search time and the convergence rate of the heuristic algorithm also increases.

Conclusion:

In this paper, gray scale histogram assisted bi-level and multi-level image thresholding problem is addressed using improved Particle Swarm Optimization (PSO), enhanced Bacterial Foraging Optimization (BFO), Lévy flight Bat Algorithm (LBA) and Brownian Bat Algorithm (BBA). Six standard gray scale test images are considered to evaluate the performance of the considered algorithms using a simulation work with the help of Matlab R2012a software. Maximization of Otsu's between class variance is adopted as the objective function for m = 2,3,4,5. From this study, it is noted that the PSO and LBA algorithm based search offers better convergence with relatively smaller iteration number and the BBA based thresholding approach offers better J_{max}, PSNR and SSIM for most of the cases compared with the alternatives considered in this study.

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