Gray-Level Histogram based Multilevel Threshold Selection with Bat Algorithm

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ABSTRACT
Image thresholding is a well known image segmentation procedure extensively attempted to obtain binary image from the gray level image. In this article, histogram based bi–level and multi-level segmentation is proposed for gray scale images using Bat Algorithm (BA). The optimal thresholds are attained by maximizing Otsu's between class variance function. The performance of BA is demonstrated by considering five benchmark (512 x 512) images and compared it with the existing algorithms such as Particle Swarm Optimization (PSO), and Bacterial Foraging Optimization (BFO) existing in the literature. The performance assessment between algorithms is carried out using prevailing parameters such as objective function, Peak Signal to Noise Ratio (PSNR), and Structural Dissimilarity (SSIM) index. The results evident that BA provides better objective function, PSNR and SSIM compared to PSO, and BFO considered in this study.

General Terms
Swarm Intelligence, Image Processing

Kewords
Histogram, Otsu, Bat algorithm, Segmentation, PSNR, DSSIM

1. INTRODUCTION
In imaging science, image segmentation is widely adapted to examine gray scale and colour images in medical discipline, navigation, environment modeling, automatic event detection, surveillance, pattern recognition, and damage detection. The advancement in digital imaging technique and computing technology has increased the potential of imaging science.

For gray scale images, thresholding is widely considered to extract key features from input image. The main objective is to enhance the key feature of an image using the best possible bi-level as well as the multilevel threshold.

A considerable number of image segmentation techniques have been proposed and implemented by most of the researchers in the literature [1, 2]. Among them, global thresholding is judged as the most efficient procedure for image segmentation, because of its simplicity, robustness, accuracy and competence [3]. Based on the segmentation scheme, global thresholding is classified as parametric and nonparametric method.

In existing parametric thresholding procedures, the statistical parameters of the image are estimated using classical approach. Most of the classical approaches has the following drawbacks; (i) computational complexity, (ii) time consuming, and (iii) the overall performance varies based on the image quality.

The nonparametric classical segmentation procedures such as Otsu, Kapur, and Kittler are very efficient and successful in the case of bi-level thresholding process [4]. When the number of threshold level increases, classical thresholding techniques require more computational time. Hence, in recent years, heuristic methods based bi-level and multi-level image thresholds has increased the interest of researchers because of the computational inefficiency of the classical exhaustive methods [5].

Recent literature illustrates that the heuristic and metaheuristic algorithms such as Particle Swarm Optimization (PSO) [6-8], Bacterial Foraging Optimization (BFO) [9, 10], Differential Evaluation (DE) [11,12], Artificial Bee Colony (ABC) [13], and Cuckoo Search (CS) [14] are widely considered for optimal multilevel image segmentation problems to enhance the outcome.

In this paper, the Bat Algorithm (BA) proposed by Xin-She Yang is considered [15-17]. The algorithm is allowed to explore the 'm' dimensional search universe, until Otsu's between-class variance function reaches a maximal value. Proposed technique is tested on five standard 512x512 sized test images and compared with the Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization (BFO) based image segmentation techniques.

The performance of considered algorithms has been evaluated using the gray-level histogram of the test images. The statistical analysis of the obtained result evident that, BA based segmentation procedure shows improved result that PSO and BFO based methods. For bi-level and multi–level segmentation process, the search time taken by BA is less compared to BFO.

The remaining part of the paper is organized as follows: overview of Otsu based segmentation procedure is discussed in section 2. The heuristic algorithm considered in this paper is discussed in section 3. Section 4 presents a brief description of the performance measures. The research findings are discussed in section 5. Section 6 provides conclusion of the present research work.

2. METHODOLOGY
The classical and optimization algorithm based thresholding methods existing in the literature are employed to find the best possible threshold in the segmented histogram by satisfying some guiding criterions. Otsu based image thresholding is initially proposed in 1979 [18]. This method presents the optimal values by maximizing the objective function. In this

work, Otsu's nonparametric segmentation method known as between-class variance is considered to identify the optimal image thresholds. A detailed description of the between-class variance method could be found in [19].

In bi-level thresholding (for m = 2), input image is divided into two classes such as C_0 and C_1 (background and objects, or vice versa) 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 distributions for the gray levels C_0 and C_1 can be expressed as;

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

where $\omega_0(t) = \sum_{i=0}^{t-1} p_i$, $\omega_1(t) = \sum_{i=t}^{L-1} p_i$ and L=256

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

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

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;

$$Maximize\ J(t) = \sigma_0 + \sigma_1 \qquad (3)$$

where $\sigma_0=\omega_0(\mu_0-\mu_T)^2$ and $\sigma_1=\omega_1(\mu_1-\mu_T)^2$

The above discussed procedure can be extended to a multi-level thresholding problem for various '*m*' values as follows;

Let us consider that there are *'m'* thresholds (t_1, t_2, …, t_m), which divide the input 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 the multi-level thresholding problem can be expressed as;

$$J_{max}(t) = \sigma_0 + \sigma_1 + \ldots + \sigma_m \qquad (4)$$

where $\sigma_0=\omega_0(\mu_0-\mu_T)^2, \sigma_1=\omega_1(\mu_1-\mu_T)^2, \ \ldots, \ \sigma_m=\omega_m(\mu_m-\mu_T)^2$

In this paper, objective functions are assigned for m=2, m=3, m=4, and m=5.

3. HEURISTIC ALGORITHMS

Literature evident that, in the past decade, heuristic algorithms are successfully implemented to solve variety of engineering optimization problems [20-23, 29,30].

3.1 Particle Swarm Optimization

PSO is an evolutionary optimization technique, developed due to the inspiration of the social activities in flock of birds and school of fish [24].

The PSO algorithm has two basic equations such as Velocity update and position update equation as presented in Eqn. 5 and 6 respectively.

$$V_i(t+1) = W^t.V_i^t + C_1R_1(P_i^t - S_i^t) + C_2R_2(G_i^t - S_i^t) \qquad (5)$$

$$X_i(t+1) = X_i^t + V_i(t+1) \qquad (6)$$

where W^t – inertia weight = 0.75, V_i^t - current velocity of particle, $V_i(t+1)$ - updated velocity of particle, X_i^t - current position of particle, $X_i(t+1)$ - updated position of particle, R1, R2 are the random numbers [0,1], and C1 = C2 = 2.1 [25].

3.2 Bacterial Foraging Optimization

BFO is a nature inspired stochastic search technique based on mimicking the foraging behavior of E. coli bacteria [26]. Due to the merits such as high computational efficiency, easy implementation and stable convergence, it is widely applied to solve a range of complex engineering optimization problems.

BFO algorithm discussed by Rajinikanth and Latha (2012a) is adapted in this work [26].

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 = $\frac{N_c}{N}$.

The main advantage of EBFO compared to the classical BFO is, the number of initializing parameters to be assigned for the search in EBFO is reduced to just two i.e. N (E. Coli size) and D (search dimension).

3.3 Bat Algorithm

The existing Bat Algorithm (BA) was based on the echolocation or bio-sonar characteristics of microbats. BA was developed by modeling the navigating and hunting manners of bats. The main dealings of Bats when finding/hunting a prey is, it will tend to diminish the loudness and amplify the rate of emitted ultrasonic sound signal when they hunt prey.

The classical BA has three mathematical models such as velocity update equation, position update equation, and frequency vector as given below;

Velocity update: $V_i(t+1) = V_i(t) + (X_i(t) - Gbest)F_i \qquad (7)$

Position update: $X_i(t+1) = X_i(t) + V_i(t+1) \qquad (8)$

Frequency vector: $F_i = F_{\min} + (F_{\max} - F_{\min})\beta \qquad (9)$

where β is a random number in the range [0,1]. From Eqn.7, it is noted that, the velocity update mainly relies on frequency vector value.

When the optimization search is initiated, new solution for each bat in the search universe is generated based on;

$$X_{new} = X_{old} + \varepsilon A^{t} \quad (10)$$

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

The minimum and maximum value of the loudness variable A is chosen as A_0 = 10, and A_{min} =1 (which decay in steps of 0.1).
The other equations available in the BA are presented below;

$$A_i(t+1) = \alpha A_i(t) \quad (11)$$

$$r_i(t+1) = r_i(0)[1-\exp(-\gamma t)] \quad (12)$$

where the constants α, and γ are assigned as; α = γ = 0.75.
A detailed analysis of the bat algorithm could be found in [27, 28].

4. IMPLEMENTATION

The multi-level thresholding problem deals with finding optimal thresholds within the gray scale range [0, L−1] that maximize a fitness criterion *J(t)*. Otsu's between class variance function is employed to find the threshold values. The search dimension of the optimization problem is assigned based on the number of thresholds (m) considered. In this paper, optimal multi-level thresholding has been carried out by an unsupervised global-level nonparametric approach.

In this work, LF driven BFO algorithm is employed to find the optimal threshold values by maximizing the Otsu's objective function. Fig. 1 depicts the flow chart of the proposed work.

The performance of the hybrid algorithm is assessed using the well known parameters such as peak-to-signal ratio (PSNR) and structural dissimilarity indices (DSSIM) [6].

The PSNR is mathematically represented as;

$$\text{PSNR(x,y)} = 20\log_{10}\left(\frac{255}{\sqrt{MSE(x,y)}}\right);\text{dB} \quad (13)$$

where MSE – Mean Square Error between original and segmented image.

The SSIM is normally used to estimate the image quality and inter dependencies between the original and processed image.

$$\text{SSIM(x, y)} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x{}^2 + \mu_y{}^2 - C_1)(\sigma_{x^2} + \sigma_{y^2} + C_2)} \quad (14)$$

where μ_x = average of x, μ_y = average of y, σ_x^2 = variance of x, σ_y^2 = variance of y, σ_{xy} = covariance of x and y, C_1= $(k_1L)^2$ and C_2= $(k_1L)^2$ stabilize the division with weak denominator, L = 256, k_1 = 0.01, and k_2 = 0.03.

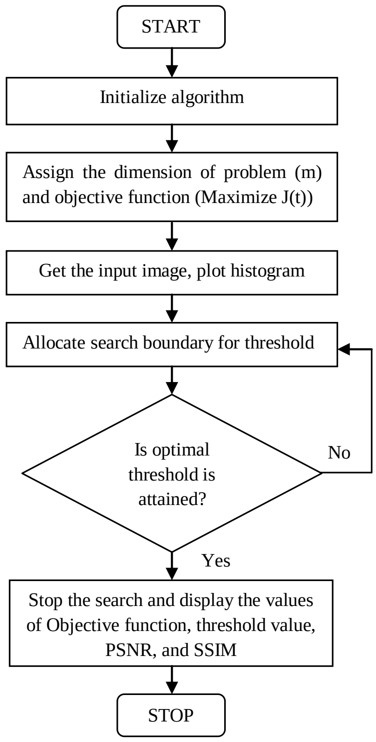


Fig. 1: Flow chart of segmentation method

Structural dissimilarity (DSSIM) is a distance metric derived from SSIM (though the triangle inequality is not necessarily satisfied).

$$DSSIM(x,y) = \frac{1-SSIM(x,y)}{2} \quad (15)$$

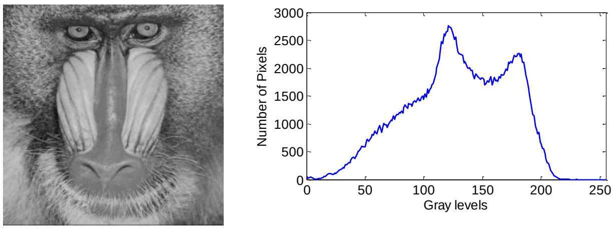
5. RESULTS AND DISCUSSIONS

Otsu guided, Bat algorithm based multi-level thresholding techniques have been tested on different standard 512 x 512 test images such as Mandrill, Bridge, Livingroom, Crane and Bee. For the PSO, BFO, and BA, the total population size is assigned as 20, and the total number of run for the search process is chosen as 250.

Simulation work is performed on a work station with an AMD C70 Dual Core 1 GHz CPU with 4GB of RAM and equipped with MATLAB R2010a software. During the experiment, each image is examined with a number of thresholds such as m = 2 to 5. The simulation study is repeated seven times individually and the best value among the search is recorded as the optimal threshold value.

Initially the PSO, BFO, and BA based optimization is tested on the Mandrill image.

Fig 2. (a) represents the original gray scale test image, and 2. (b) shows the histogram. For this image, the span of gray level is from 8 to 212.



(a) Mandrill (b) Histogram

Fig 2: Orignal image and its histogram

Initially, BA based search is proposed for m = 2. The search process is repeated seven times and the optimal threshold values and the corresponding performance measures such as objective function (OF) = $J_{max}(t)$, total number of iterations taken to terminate the search process, PSNR in dB, and DSSIM values are presented in Table 1. For bi-level thresholding, Trial 2 offered better performance measures compared to other trials. Hence, Trial 2 value is chosen as the best possible value. Similar procedure is repeated using PSO and BFO algorithms and corresponding performance measure values are recorded (refer Table 5).

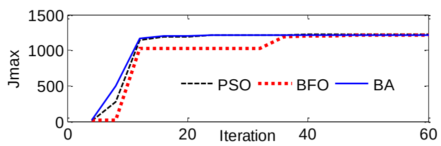


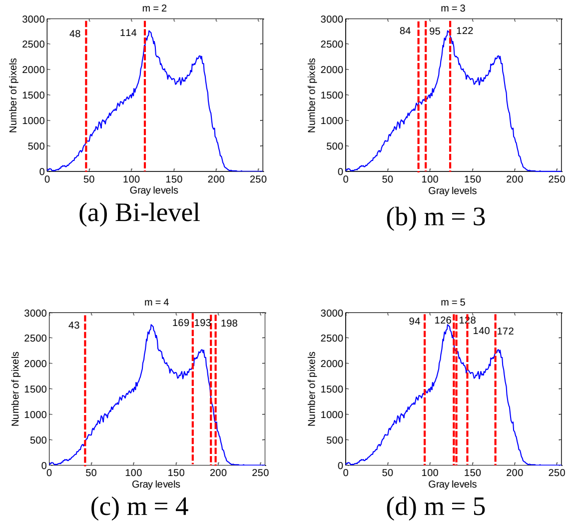
Fig 3. Convergence of search for mandrill image

Convergence of optimization search for bi-level thresholding is presented in Fig 3. From this, it is observed that, search efficiency of the BA is superior compared to PSO and BFO. The BA algorithm offered the optimal threshold at 25^{th} iteration, where as the PSO and BFO converged at 27^{th} and 38^{th} iterations respectively.

The above discussed segmentation procedure is then implemented on the Mandrill image for m = 3, 4, and 5 using BA, PSO, and BFO.

- Table 2. presents the BA based optimized threshold value and corresponding performance measure values for m=3.
- Table 3. shows best possible threshold value and performance measure values for m=4.
- Table 4. presents optimal threshold values and performance measure for m=5.

In above Tables, the highlighted column values are chosen as the best value among seven trials.



(a) Bi-level (b) m = 3

(c) m = 4 (d) m = 5

Fig. 4 Optimal threshold for the mandril image for various 'm' values

Fig 4. Illustrate the optimal threshold values of gray scale mandrill image. Fig. 4 (a) shows gray level histogram of mandrill image for m = 2. Fig. 4 (b), (c), (d) shows the gray level histogram for m = 3, 4, and 5 respectively.

Gray-level histogram based bi-level and multi-level threshold selection procedure is then extended to 512x512 sized gray scale images such as Bridge, Living room, Crane, and Bee. The major reason to select the above mentioned images is, these images have a randomly varying pixel level with respect to the gray levels.

The histogram of these images is more oscillatory, compared to histogram of mandrill image. Finding an optimal threshold on the complex histogram is a challenging task.

Initially, we attempted the heuristic algorithm based search on the gray–level histogram of the bridge image. The histogram pattern is very complex compared to other images. Hence the convergence time taken by the heuristic algorithms is slightly larger than Crane and Bee image. Later, the procedure is extended for other gray scale images. The thresholded images (for m=2,3,4, and 5) are illustrated in Table 6, and the corresponding performance measures and optimal threshold values are presented in Table7 and Table 8 respectively.

From Table 7, it is observed that, BA offers better objective function, PSNR, and DSSIM compared to PSO and BFO. Fig. 5 to Fig.8 shows the convergence of optimization search for the considered test images when m =2. For Bridge, Living room, and Bee images, the BA based search convergence is better. Whereas for Crane image, PSO shows faster convergence than BA and BFO.

Table 1. Segmented Mandrill image and its performance measures for m = 2

Mandrill (m = 2)	**Trial 1**	**Trial 2**	**Trial 3**	**Trial 4**	**Trial 5**	**Trial 6**	**Trial 7**
							
OT	100, 124	**48,114**	108, 134	121,129	97,120	49, 110	131,146
OF	1216.75	**1219.05**	1213.83	1211.40	1207.64	1217.34	1217.33
Iteration	28	**25**	33	22	34	47	19
PSNR	24.043	**24.726**	24.377	24.720	23.207	24.472	23.793
DSSIM	0.1740	**0.1664**	0.1763	0.1694	0.1803	0.1701	0.1795

Table 2. Segmented Mandrill image and its performance measures for m = 3

Mandrill (m = 3)	**Trial 1**	**Trial 2**	**Trial 3**	**Trial 4**	**Trial 5**	**Trial 6**	**Trial 7**
							
Optimal threshold	67, 115, 144	95, 156, 191	52, 76, 124	67, 124, 162	146, 159, 195	68, 73, 219	**84, 95, 122**
OF	1205.33	1197.52	1217.33	1213.85	1189.55	1163.22	**1218.01**
Iteration	73	50	44	39	58	82	**67**
PSNR	24.036	23.992	24.228	24.104	23.116	23.063	**24.705**
DSSIM	0.1643	0.1672	0.1692	0.1753	0.1683	0.1783	**0.1619**

Table 3. Segmented Mandrill image and its performance measures for m = 4

Mandrill (m = 4)	**Trial 1**	**Trial 2**	**Trial 3**	**Trial 4**	**Trial 5**	**Trial 6**	**Trial 7**
							
Optimal threshold	100, 148, 156, 158	73, 128, 138, 211	112, 126, 131, 133	111, 113, 114, 154	**43, 169, 193, 198**	38, 109, 127, 182	98, 112, 121, 157
OF	1218.16	1217.34	1218.58	1210.52	**1218.93**	1218.72	1218.76
Iteration	114	79	92	63	**87**	105	102
PSNR	25.185	25.221	24.974	24.953	**25.745**	25.072	24.982
DSSIM	0.1602	0.1587	0.1615	0.1631	**0.1570**	0.1595	0.1618

Table 4. Segmented Mandrill image and its performance measures for m = 5

Mandrill (m = 5)	**Trial 1**	**Trial 2**	**Trial 3**	**Trial 4**	**Trial 5**	**Trial 6**	**Trial 7**
							
Optimal threshold	15, 127, 154, 164, 166	**94, 126, 128, 140, 172**	103, 125, 139, 154, 166	16, 71, 120, 125, 129	100,108, 126, 133, 177	119,122, 124, 129, 152	57, 118, 124, 130, 133
OF	1219.05	**1219.07**	1218.73	1218.72	1215.83	1219.07	1218.93
Iteration	57	**82**	121	76	95	108	79
PSNR	25.017	**25.807**	25.788	25.591	25.771	25.783	25.633
DSSIM	0.1603	**0.1552**	0.1591	0.1595	0.1599	0.1586	0.1581

Table 5. Performance measure for PSO and BFO algorithm

m	**PSO**					**BFO**				
	OF	**Iteration**	**St.D**	**PSNR**	**DSSIM**	**OF**	**Iteration**	**St.D**	**PSNR**	**DSSIM**
2	1207.3	27	0.0015	22.042	0.1759	1218.0	38	0.0019	22.027	0.1635
3	1221.4	48	0.0712	23.916	0.1634	1220.6	64	0.0037	23.054	0.1648
4	1229.5	51	0.0805	24.060	0.1681	1227.8	122	0.0523	24.368	0.1626
5	1227.0	74	0.0814	23.521	0.1595	1231.1	146	0.0495	24.503	0.1617

Table 6. Test images, histogram, and segmented images

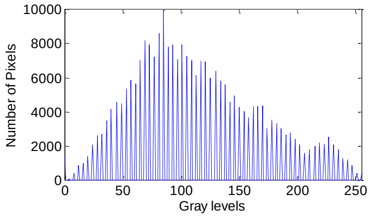
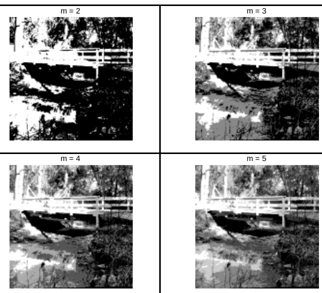
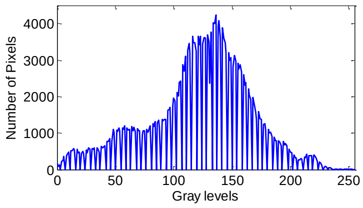
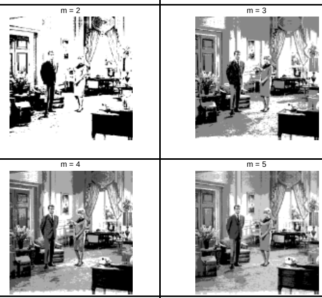
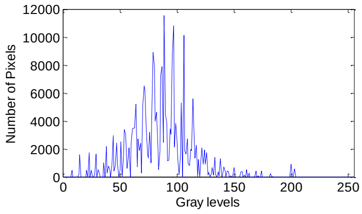
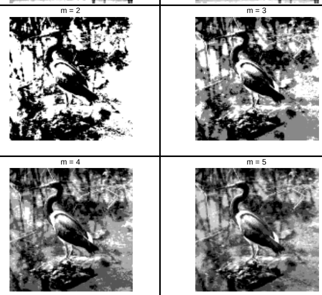
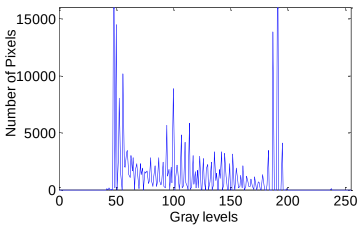
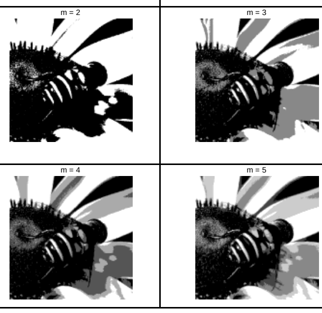
Image	Histogram	Multi threshold Images
 Bridge		
 Living room		
 Crane		
 Bee		

Table 7. Performance measure for PSO, BFO, and BA for test images

Image	m	Objective function			Iterations			PSNR			DSSIM		
		PSO	**BFO**	**BA**	**PSO**	**BFO**	**BA**	**PSO**	**BFO**	**BA**	**PSO**	**BFO**	**BA**
Bridge	2	2062.0	2063.4	2063.9	93	121	47	15.28	16.03	16.11	0.3173	0.2014	0.1863
	3	2068.3	2071.1	2072.7	88	125	53	15.72	16.16	16.82	0.2018	0.1973	0.1735
	4	2081.8	2082.4	2079.3	102	135	94	18.27	19.02	19.11	0.1835	0.1903	0.1722
	5	2076.1	2088.8	2091.2	113	149	108	19.35	20.66	20.81	0.1789	0.1825	0.1681
Living room	2	1246.4	1248.1	1246.8	39	85	32	16.36	16.29	16.37	0.1972	0.1925	0.1832
	3	1248.3	1247.0	1248.5	84	97	77	16.92	17.03	17.31	0.1770	0.1732	0.1628
	4	1259.1	1255.8	1256.3	107	132	89	18.24	19.05	19.16	0.1701	0.1711	0.1620
	5	1256.5	1258.4	1259.1	118	149	102	19.36	19.72	20.04	0.1601	0.1612	0.1603
Crane	2	403.57	404.06	404.62	22	48	29	12.29	13.20	13.92	0.1826	0.1831	0.1725
	3	408.23	410.06	409.84	57	61	55	15.83	17.28	17.99	0.1723	0.1755	0.1708
	4	410.72	411.02	412.28	85	109	73	16.29	16.64	18.00	0.1682	0.1671	0.1655
	5	409.96	410.50	411.27	103	120	94	18.43	18.92	18.99	0.1631	0.1664	0.1633
Bee	2	1925.6	1924.9	1925.8	36	71	19	17.01	18.53	18.92	0.1771	0.1802	0.1751
	3	1929.1	1930.9	1929.5	61	83	49	19.23	19.03	19.67	0.1700	0.1752	0.1679
	4	1932.7	1931.6	1933.1	65	102	51	22.34	23.91	29.94	0.1681	0.1705	0.1624
	5	1933.7	1934.1	1934.3	95	116	77	24.00	24.71	24.85	0.1654	0.1692	0.1621

Table 8. Optimal bi-level and multi level threshold values

	m	PSO	BFO	BA
Bridge	2	32,141	43,150	38,146
	3	38,86,147	52,116,193	44,120,195
	4	33,86,142,205	47,74,138,210	36,81,144,211
	5	40,64,138,162,206	47,93,117,182,206	38,85,131,176,212
Living room	2	71, 148	81,147	68,151
	3	48,132,183	62,128,183	53,116,192
	4	56,87,130,164	44,73,141,172	52,96,120,189
	5	49,81,106,148,182	50,74,108,142,190	46,83,137,150,184
Crane	2	58,148	52,141	56,144
	3	42,74,130	51,92,138	38,94,126
	4	33,72,97,126	28,69,83,130	26,58,92,110
	5	30,51,82,97,138	36,80,101,132,144	28,74,96,120,138
Bee	2	72,193	68,194	70,195
	3	54,95,188	62,115,168	58,130,184
	4	51,83,152,174	66,92,141,192	60,88,133,182
	5	54,101,156,171,188	63,82,112,154,169	54,92,110,144,171

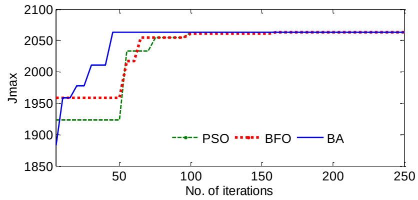


Fig 5: Convergence of search for Bridge image

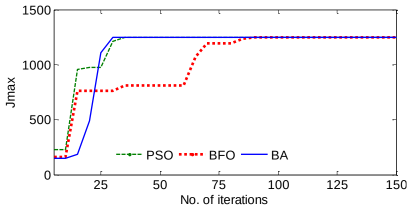


Fig 6. Convergence of search for Living room image

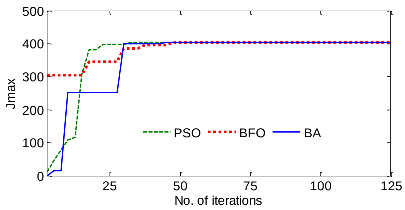


Fig 7. Convergence of search for Crane image

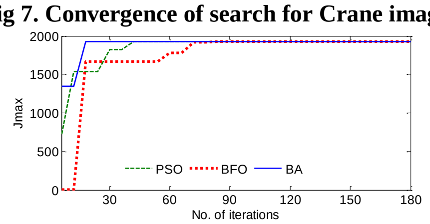


Fig 8. Convergence of search for Bee image

6. CONCLUSION

In this study, gray scale histogram based optimal bi-level and multi-level image thresholding problem is discussed using PSO, BFO, and Bat algorithm. Maximization of Otsu's between class variance function is chosen as the objective function. In order to evaluate the performance of considered heuristic algorithms, five gray scale test images are examined.

When the assigned threshold level is two (m = 2), the number of iteration taken by the algorithm is small and the iteration value increases with the increase in threshold levels. From this study, the observation is that, BA offers better performance compared to PSO and BFO algorithms considered in this study.

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