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Optimal Multi-level Image Thresholding using Lévy Flight driven Algorithms – A Study with Bat, Cuckoo Search and Firefly Algorithm

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ABSTRACT

In recent years, a plethora of soft computing methods are proposed by the researchers to find optimal solutions for constrained and unconstrained optimization problems. Among them, Lévy Flight (LF) driven algorithms are widely adopted by most of the researchers. In this work, we considered the recent LF based algorithms, such as the Bat Algorithm (BA), Cuckoo Search (CS) and Firefly Algorithm (FA) to solve optimal multi-level image thresholding problem using Otsu. Optimal thresholds for the gray scale images are reached by analyzing histogram of the image. Maximization of Otsu's between class variance function is chosen as the objective function. The performances of the LF based algorithms are assessed by considering eight standard (512 x 512) test images. The performance appraisal between the LF algorithms are carried using the well known quality measures, such as maximal objective function, Root Mean Squared Error, Peak Signal to Noise Ratio, and convergence of optimization search. The result evident that, for most of the test images, the LF driven FA offers better overall result compared with the BA and CS.

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INTRODUCTION

In image processing application, segmentation acts as a primary and important procedure in the analysis and examination of gray and color images. For gray scale images, segmentation process helps to separate an image into non-overlapping, homogenous regions having similar objects (Akey, 2013). In general, the gray level histogram of the image is bi-model. Hence, the image objects are clearly distinguishable from the background by simply choosing a threshold value by considering the valley between two peaks of the histogram. But, in the real cases, the gray level histograms of the real time images are mostly multimodal and identifying the accurate position of distinct valleys in multimodal histograms is quite difficult (Sathya and Kayalvizhi, 2010). Due to these reasons, solving the multi-level thresholding problem is emerged as the significant area of research in recent years (Sathya and Kayalvizhi, 2011; 2012).

Over the years, several image segmentation methods have been proposed and executed in the literature (Lee *et al*., 1990; Pal and Pal, 1993; Sezgin and Sankar, 2004). In segmentation, the input image is separated into object and background. Based on the performance evaluation procedure, the segmentation methods are classified as supervised and unsupervised procedures. Unsupervised methods are preferable in real-time processing because they do not require a manually segmented image (Raja *et al*., 2014).

Image thresholding is considered as the most preferred practice out of all the existing image segmentation methods, because of its simplicity, robustness, exactness and capability (Rajinikanth *et al*., 2014a; 2014b). Traditional segmentation methods work well for a bi-level thresholding problem, when the number of threshold level increases, complexity of the thresholding problem will also increase and the traditional method requires more computational time because of multi-level complexity. Hence, in recent years, heuristic and metaheuristic algorithms based bi-level and multi-level image thresholding procedure is widely proposed by the researchers.

Horng (2011) proposed Artificial Bee Colony (ABC) algorithm based heuristic approach to solve the multi-level image thresholding problem for gray scale images using Otsu. Sathya and Kayalvizhi (2010; 2011) implemented Particle Swarm Optimization (PSO) and Bacterial Foraging Algorithm (BFA) based Otsu and validated the proposed method with the Genetic Algorithm. Further, they proposed a Modified Bacterial

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Foraging (MBF) approach to solve the gray scale thresholding problem. Akay (2013) presented a detailed study on multi-level image thresholding using Kapur's entropy and Otsu's between class variance function using most successful heuristic approaches, such as PSO and ABC. SriMadhava Raja *et al*. (2014) presented a detailed study on gray scale image thresholding using Otsu and Firefly Algorithm. Recently, Rajinikanth *et al*. (2014) presented a detailed study about, PSO, BFO and Bat Algorithm (BA) based image thresholding using Otsu. Similar approaches are widely available in the image segmentation literature (Agarwal *et al*., 2013; Alihodzic and Tuba, 2014; Charansiriphaisan *et al*., 2013; Ghamisi *et al*., 2012, Panda *et al*., 2013).

In this paper, the heuristic algorithms proposed by Yang (2008) are considered. The most successful recent algorithms, such as Bat Algorithm (Yang, 2010), Cuckoo Search (Yang and Deb, 2009) and Firefly Algorithm (Yang, 2009;2010) are considered in the proposed gray scale image thresholding problem. The most victorious Lévy Flight (LF) search pattern is considered in this work. The proposed procedure is tested on standard test images (512 x 512) and its performance is evaluated using measures, such as algorithm convergence, maximized objective function value, Root Mean Squared Error (RMSE), and Peak Signal to Noise Ratio (PSNR) in dB.

The paper is structured as follows: Section 2 presents the Otsu based bi-level and multi-level thresholding problem. Section 3 presents the overview of the heuristic algorithms in this study and the implementation is discussed in Section 4. Experimental results are assessed and presented in Section 5. Conclusion of the research work is specified in section 6.

Methodology:

Otsu's image thresholding procedure was initially proposed in 1979 (Otsu, 1079). Due to its simplicity and better segmentation capability, it is widely adopted by most of the researchers to segment the gray scale and colour images (Ghamisi *et al*., 2012; 2013; 2014). In this method, maximization of Otsu's between class variance function is used to obtain the best possible threshold values for both the bi-level and multi-level segmentation operations.

A detailed description of Otsu's method could be found in the literatures and this process is defined as follows:

For a given image, let there be L intensity levels in the range {0,1,2,…, L-1}. Then, it can be defined as;

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

The overall mean of each element of the image is calculated as;

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

The multi-level thresholding presents m-1 threshold levels t_j^c, where j = 1,2,…,m-1, and the action is executed as;

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

The probabilities of occurrence w_j^C of classes D_i^c,…, D_m^c are given by;

$$w_j^C = \begin{cases} \sum_{i=0}^{t_j^C} p_i^C, & j=1 \\ \sum_{i=t_j^C-1}^{t_j^C} +1\ p_i^C, & 1 < j < m \\ \sum_{i=t_j^C-1}^{L-1} +1\ p_i^C, & j = m \end{cases} \tag{4}$$

The mean of each class μ_j^C can then be calculated as ;

$$\mu_j^C = \begin{cases} \sum_{i=0}^{t_j^C} \frac{p_i^C}{w_j^C q}, & j = 1 \\ \sum_{i=t_{j-1}^C+1}^{t_j^C} \frac{p_i^C}{w_j^C}, & 1 < j < m \\ \sum_{i=t_{j-1}^C+1}^{L-1} \frac{p_i^C}{w_j^C}, & j = m \end{cases} \quad (5)$$

Then, Otsu's between-class variance of each component can be represented as;

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

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

The multi-level thresholding is then reduced to an optimization problem to search for t_j^C, that maximize the objective functions of each image component C can be defined as:

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

Heuristic Algorithms:

Lévy Flight Strategy:

In heuristic algorithms, convergence speed and optimization accuracy mainly depends on the guiding parameters which help to update the agent values. Most of the preliminary heuristic algorithms are guided by the randomization operator. Due to the randomization parameter, the optimization accuracy and the convergence will not be in expected level in most of the search cases. Hence, in recent years Lévy Flight (LF) and Brownian Distribution (BD) based search pattern is widely adopted to update the agent positions (Sri Madhava Raja *et al*, 2014). In the proposed work, LF is considered to update the agent positions in the heuristic algorithms.

LF is a random walk with a sequence of arbitrary steps and is conceptually similar to the search path of a foraging animal (Sri Madhava Raja *et al*, 2013). In LF, the flight span and the length between two successive changes in direction are drawn from a probability distribution. A detailed explanation of LF is discussed in the book by Yang (Yang, 2008). Lévy flight is superdiffusive markovian process, whose step length is drawn from the Lévy distribution in terms of a simple power-law formula;

$L(s) \sim |s|^{-1-\beta}$ where $0 < \beta \le 2$ (8)

Lévy flight = $L_F(s) = A.|s|^{1/\beta}$ (9)

Where

$$A = \beta\Gamma(\beta)\sin\left(\frac{\beta\pi}{2}\right)\frac{1}{\pi} \quad (10)$$

where A is the random variable, β is the spatial exponent, α is the temporal exponent, and $\Gamma(\beta)$ is a Gamma function.

Bat Algorithm:

The Bat Algorithm (BA) is based on the bio-sonar characteristics of microbats. BA was anticipated by modelling the navigating and hunting potential of bats (Yang, 2010). A detailed examination on the BA algorithm can be found in (Yang, 2013).

The BA was developed based on the following assumptions (Kotteeswaran and Sivakumar, 2013):

- All the bats use echolocation to sense distance, prey, and background barriers.
- The bats will fly with a velocity V_i, at position X_i with an emitted frequency f_{min}, varying wavelength λ and a loudness A_o. During the search, the bats will automatically adjust the frequency, wavelength and pulse emission rate $r \in [0,1]$ based on the target distance.
- Along with the above said parameters, the loudness also varies from a large A_o value to a constant A_{min} value.

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:

$$V_i(t+1)=V_i(t)+(X_i(t)-Gbest)F_i \quad (11)$$

$$X_i(t+1)=X_i(t)+V_i(t+1) \quad (12)$$

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

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:

$$X_{new}=X_{old}+\varepsilon A^t \quad (14)$$

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:

$$A_i(t+1)=\alpha A_i(t) \quad (15)$$

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

where α and γ are constants typically assigned with a numeral value of 0.75 (Rajinikanth *et al*., 2014).

Cuckoo Search Algorithm:

Cuckoo Search (CS) is one of the successful algorithms, proposed by Yang and Deb in 2009. This algorithm is based on the breeding tricks of parasitic cuckoos (Yang and Deb, 2009). CS algorithm is developed based on the following rules:

- Each cuckoo lays an egg and dumps in a randomly chosen nest
- The nest with high survived egg will be carried over to the next generation. Cuckoo's egg generally hatches several days before than the host's eggs. The cuckoo chick grows faster and expels the host's eggs and chicks.
- In a search universe, the number of host nest is fixed. The host bird discovers the cuckoo's egg with a probability $p_a \in [0,1]$. When the host identifies the egg, it may remove it from nest, or simply abandon the nest and build a new nest.

In CS, during the optimization search, the new solution ($X_i^{(t+1)}$) mainly depends on the old solution ($X_i^{(t)}$) and the search guiding procedure (Yang and Gandomi, 2012). In this work, the following expressions are considered to find the new solution;

$$X_i^{(t+1)}=X_i^{(t)}+\alpha \oplus LF \quad (17)$$

where α > 0 is the succeeding step.

Firefly Algorithm:

Firefly algorithm is also proposed by Yang in 2009. This algorithm is developed by imitating the flashing illumination patterns generated by invertebrates such as glowworm and firefly, which generates chemically produced light from their lower abdomen. This bioluminescence with varied flashing patterns generated by glowworm/firefly is used to establish communication between two neighboring insects, to search for pray and also to find mates (Yang, 2009; 2010).

The classical FA is developed by taking into account the following conditions:

(i) All the fireflies are unisex and one firefly will be attracted with other nearest firefly regardless of their sex.

(ii) The attractiveness between two fireflies is proportional to the luminance.

(iii) The brightness of a firefly is somehow related with the analytical form of the objective function assigned to guide the search process.

The overall performance (exploration time, speed of convergence, and optimization accuracy) of the FA depends on the cost function, which monitors the optimization search. For a maximization problem, luminance of a firefly is considered to be proportional to the value of cost function, (ie. luminance = objective function).

The chief parameters which decide the efficiency of the FA are the variations of light intensity and attractiveness between neighboring fireflies (Kotteeswaran and Sivakumar, 2014).

Variation in luminance can be analytically expressed with the following Gaussian form:

$$I(r)=I_0 e^{-\gamma d^2} \quad (18)$$

where I = new light intensity, I_0 = original light intensity, and γ = light absorption coefficient.

The attractiveness towards the luminance can be analytically represented as:

$$\beta=\beta_0 e^{-\gamma d^2} \quad (19)$$

where β = attractiveness coefficient, and β_0 = attractiveness at r = 0.

The above equation describes a characteristic distance $\Gamma = 1/\sqrt{\gamma}$ over which the attractiveness changes significantly from β_0 to $\beta_0 e^{-1}$. The attractiveness function $\beta(d)$ can be any monotonically decreasing functions such as the following form;

$$\beta(d) = \beta_0 e^{-\gamma d^m} \quad ,(m \geq 1) \tag{20}$$

For a fixed γ, the characteristic length becomes;

$$\Gamma = \gamma^{-1/m} \rightarrow 1, m \rightarrow \infty \tag{21}$$

Conversely, for a given length scale Γ, the parameter γ can be used as a typical initial value (that is $\gamma = 1/\Gamma m$).

The Cartesian distance between two fireflies i and j at x_i and x_j, in the n dimensional search space can be mathematically expressed as;

$$d^t_{ij} = \left\| X^t_j - X^t_i \right\|_2 = \sqrt{\sum_{k=1}^{n} (X_{j,k} - X_{i,k})^2} \tag{22}$$

In FA, the light intensity at a particular distance d from the light source X^t_i obeys the inverse square law. The light intensity of a firefly I, as the distance d increases interms of $I \propto 1/d^2$. The movement of the attracted firefly i towards a brighter firefly j can be determined by the following position update equation;

$$X^{t+1}_i = X^t_i + \beta_0 e^{-\gamma d^2_{ij}} (X^t_j - X^t_i) + \alpha . sign(rand - ½) \oplus Lévy \tag{23}$$

where, X^{t+1}_i = updated position of firefly, X^t_i = initial position of firefly, and $\beta_0 e^{-\gamma d^2_{ij}} (X^t_j - X^t_i)$ = attraction between fireflies.

In the proposed work, a comparative investigation is presented between LF driven BA, CS, and FA.

Implementation:

Heuristic algorithm based optimal multi-level thresholding problem is performed in this paper. The procedure deals with finding best possible threshold values within the gray scale histogram range [0, L−1] by maximizing Otsu's between class variance function. In this procedure, the dimension of the optimization search is assigned based on the number of threshold (m) values. This procedure is executed using the LF driven BA, CS and FA.

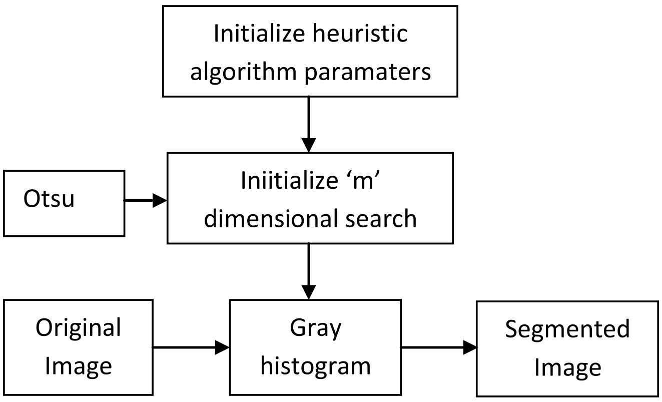

Fig. 1: Block diagram representation of implementation process

Implementation of the proposed image segmentation procedure is depicted in Fig 1. This procedure has the following steps:

Step 1: Initialize the heuristic algorithm with appropriately chosen algorithm parameters
Step 2: Assign the objective function to be maximized
Step 3: Assign the dimension of search (optimal thresholds to be identified)
Step 4: Start the search, compute the objective function. Repeat the search based on the 'm' value until the total number of iteration or objective function is maximized.

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Step 5: If optimal values are attained, stop the search, display the segmented image, threshold values, and the objective function value.

Step 6: Compute and display the performance measure values such as RMSE and PSNR.

The performance of multi-level segmentation procedure is assessed using well known image quality measures, such as maximal between-class variance, Root Mean Squared Error (RMSE) and Peak Signal to Noise Ratio (PSNR) in dB.

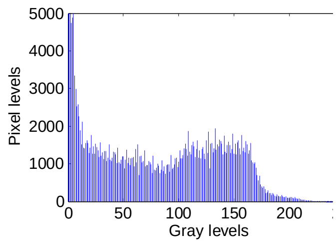
PSNR is used to find the similarity of the segmented image against the original image based on the RMSE of each pixel (Akay, 2013):

$$RMSE_{(o,s)} = \sqrt{MSE_{(x,y)}} = \sqrt{\frac{1}{MN}\sum_{i=1}^{H}\sum_{j=1}^{W}[o(i,j)-s(i,j)]^2} \quad (24)$$

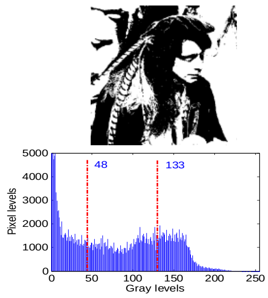
$$PSNR(o,s) = 20 \log_{10}\left(\frac{255}{\sqrt{MSE(o,s)}}\right); \text{dB} \quad (25)$$

where *o* and *s* are original and segmented images of size H x W.

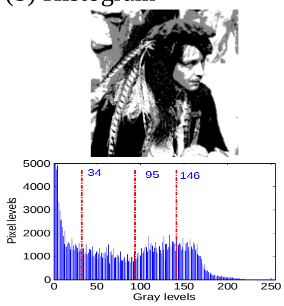
(a) Original image (Hunter)



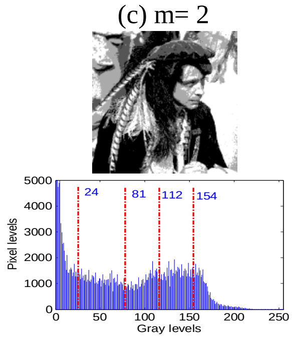
(b) Histogram



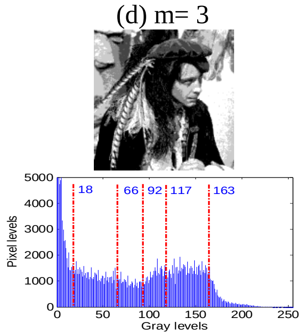
(c) m= 2



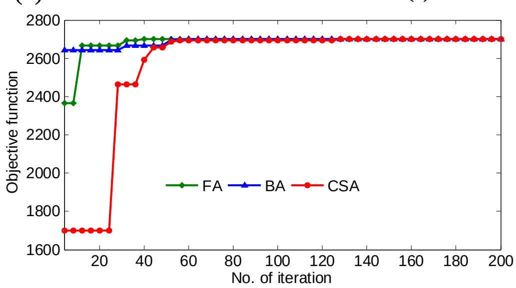
(d) m= 3



(e) m= 4



(f) m = 5



(g) Convergence of optimization search for m = 2

Fig. 2: Original and segmented Hunter image with LF driven FA

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Table 1: Original image and the corresponding gray histogram

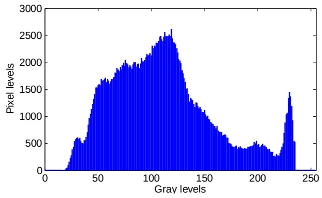
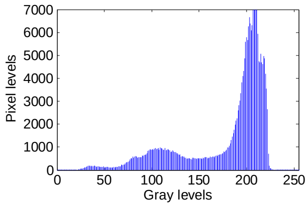
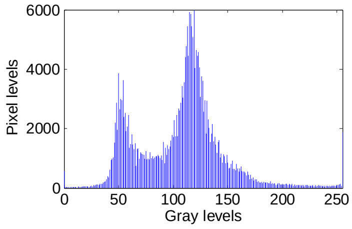
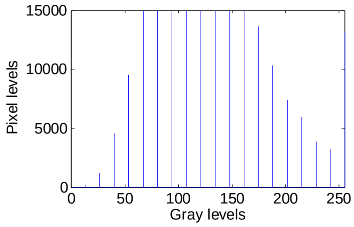
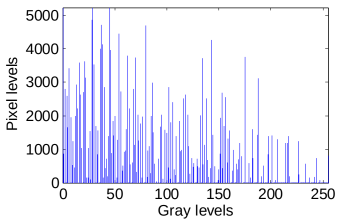
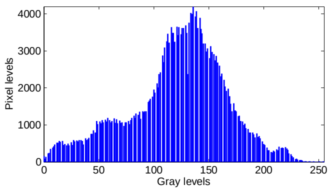
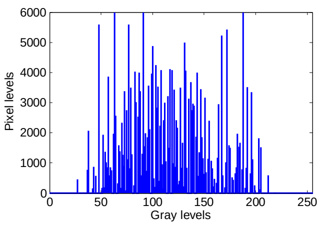
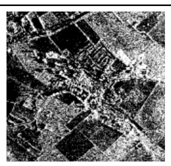
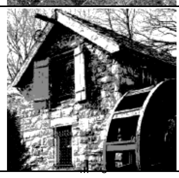
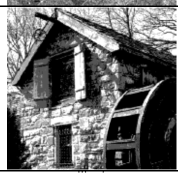
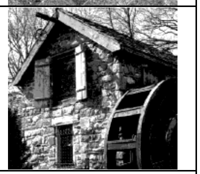
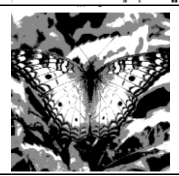
	Original Image	Histogram
Gold hill		
Jet		
Traffic		
Map		
House		
Couple		
Butterfly		

Table 2: Segmented dataset with LF driven BA

	Thresholded images			
	m = 2	m = 3	m = 4	m = 5
Gold hill				
Jet				
Traffic				
Map				
House				
Couple				
Butterfly				

RESULTS AND DISCUSSION

Otsu guided, Lévy Flight (LF algorithms based multi-level thresholding techniques have been tested on standard gray scale test images (512 x 512), such as Hunter, Goldhill, Jet, Traffic, Map, House, Couple, and Butterfly. From the grey histogram, it is noted that, Hunter, Goldhill, Jet, and Traffic offers a smooth histogram and the rest of the images (Map, House, Couple, and Butterfly) shows hastily altering pixel levels. The simulation work is executed on a work station with Intel Dual Core 1.6 GHz CPU with 2 GB of RAM and is equipped with Matlab R2010a software.

During the optimization search, population of heuristic algorithms are chosen as 25, number of iteration is allotted as 500, the search dimension is assigned as '*m*', and the stopping criterion is maximal between-class variance function. For each image, and for each *m* value, the segmentation process is repeated 15 times and the mean value among the trials is chosen as set of optimal thresholds and performance measures.

The Bat Algorithm parameters are assigned based on the work by Rajinikanth *et al*. (2014); the firefly algorithm parameters are chosen based on the work by Sri Madhava Raja *et al*. (2014) and the cuckoo search parameters are assigned based on Alihodzic and Tuba (2014).

Initially, the optimal thresholding process is implemented on the Hunter image for *m* = {2, 3, 4, 5} using the LF based BA, CS, and FA. In Fig. 2 (a, b) shows the original image and the corresponding gray level histogram. Fig. 2 (c - f) shows the segmented image and the corresponding optimal gray threshold values obtained using the BA for m = 2,3,4 and 5. Fig. 2.g shows the convergence of optimization search and from this one can observe that, the FA offers faster convergence compared with the BA and CS.

The above said procedure is repeated for the image dataset shown in Table 1 with BA, CS and FA and the corresponding result are clearly presented in Table 2,3 and 4. Table 2 shows the segmented gray scale image with BA for m = 2-5. Table 3 presents the maximized objective function value and the corresponding optimal threshold levels for various '*m*' values. Table 4 presents the vital details, such as convergence of algorithm, RMSE value and PSNR in dB.

Table 3: Maximized between- class variance function and the corresponding thresholds (mean value of trials)

	m	Objective function			Optimal thresholds		
		BA	CS	FA	BA	CS	FA
Hunter	2	2692.19	2687.23	2690.35	66,119	65,120	64,122
	3	2705.26	2710.72	2711.81	52,88,138	50,87,136	49,86,142
	4	2772.84	2791.25	2788.02	34,82,126,158	32,81,125,160	33,84,125,160
	5	2791.62	2805.28	2796.15	29,71,112,144,179	28,70,114,142,181	30,70,110,146,180
Gold hill	2	1563.82	1538.91	1567.03	88, 162	86, 165	86, 166
	3	1607.05	1584.37	1600.92	64, 141, 172	61, 140, 173	62, 138, 171
	4	1693.02	1624.73	1679.84	58, 90, 138, 180	56, 92, 136, 182	56, 89, 137, 183
	5	1710.37	1689.35	1706.92	44, 78, 152, 178, 202	43, 76, 153, 180, 200	46, 76, 150, 177, 203
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	68,100,138,184,218	67,100,140,186,220
Traffic	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	61,102,132,162,210	60,97,126,171,208
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	71,119,142,185,221	70,126,139,186,223
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	63,106,144,171,194	60,102,145,176,192
Couple	2	1247.46	1253.03	1244.92	85,148	84,150	82,151
	3	1294.43	1287.50	1294.84	72,126,162	71,124,164	68,125,164
	4	1314.38	1382.16	1307.72	61,100,132,176	60,101,134,173	57,104,138,174
	5	1391.62	1405.27	1384.76	52,96,128,144,182	50,94,126,142,184	50,93,129,146,183
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	61,101,126,170,184	62,99,126,160,185

In the proposed work, multi-level image thresholding process is proposed with the recent heuristic algorithms introduced by Yang (2008; 2009; 2010). From Table 3 and Table 4, it can be observed that, all the algorithm helps to achieve approximately similar objective function values and PSNR values. From Table 4, one can observe that, the Firefly algorithm provides faster convergence compared with the BA and CS.

Conclusion:

In this paper, bi-level and multi-level image thresholding problem is addressed using Lévy Flight (LF) driven Bat Algorithm (BA), Cuckoo Search (CS), and Firefly Algorithm (FA). Maximization of Otsu's between-class variance function is chosen as the objective function. In this work, the segmentation process is attempted for m = 2,3,4 and 5. In order to validate the performance of considered heuristic algorithms, eight standard test images are examined. The proposed segmentation procedure is validated using both the qualitative and quantitative analysis. All the algorithms offer approximately similar values for objective function, RMSE, and PSNR for the considered 'm' levels. For most of the images, the convergence of FA is better compared with the BA and CS. The future work will include the implementation of the proposed method for color image datasets.

Table 4: Performance measure values for LF driven BA,CS and FA (mean value of trials)

	m	No. of iterations			RMSE			PSNR (dB)		
		BA	CS	FA	BA	CS	FA	BA	CS	FA
Hunter	2	52	58	63	49.0603	50.1104	48.1367	14.3162	14.1322	14.4813
	3	83	77	71	32.6248	30.9737	31.0862	17.8598	18.3109	18.2795
	4	163	139	144	24.5809	23.0816	24.0005	20.3188	20.8655	20.5264
	5	186	177	162	19.9211	19.8267	18.1729	22.1445	22.1858	22.9423
Gold hill	2	38	44	27	82.1109	82.8362	81.0836	9.8428	9.7664	9.9521
	3	80	71	55	50.5738	49.7428	50.0826	14.0523	14.1962	14.1371
	4	95	97	72	40.3627	40.9366	39.9373	16.0112	15.8886	16.1032
	5	133	128	101	30.2375	31.8365	30.0365	18.5199	18.0723	18.5778
Jet	2	58	64	48	68.9070	63.9366	62.7919	11.3655	12.0158	12.1727
	3	88	74	69	45.6958	46.1281	46.9643	14.9333	14.8515	14.6954
	4	137	147	123	28.8766	27.9024	28.8831	18.9199	19.2180	18.9179
	5	139	153	143	23.3971	23.7927	23.0061	20.7476	20.6019	20.8939
Traffic	2	48	52	46	66.2661	66.5404	68.1272	11.7050	11.6691	11.4644
	3	84	72	93	61.0261	60.8152	60.4393	12.4205	12.4506	12.5044
	4	122	129	113	59.0528	52.9365	50.8653	12.7060	13.6557	14.0024
	5	166	176	140	44.0736	41.6378	42.6053	15.2472	15.7410	15.5415
Map	2	48	58	36	71.0126	70.2562	69.7464	11.1041	11.1971	11.2604
	3	82	73	68	42.6722	41.5829	43.0065	15.5279	15.7525	15.4601
	4	136	116	108	30.3229	31.0377	29.5925	18.4954	18.2930	18.7072
	5	205	194	188	24.3621	23.9366	24.1110	20.3965	20.5496	20.4865
House	2	57	61	33	49.4705	41.8813	41.0400	14.2416	15.6908	15.8611
	3	77	68	57	42.2411	40.5408	40.7702	15.6106	15.9700	15.9210
	4	116	141	122	37.4604	34.4403	33.8005	16.6514	17.3800	17.5509
	5	184	196	156	35.5207	32.9507	30.3521	17.1208	17.7705	18.4803
Couple	2	36	43	41	56.1988	55.2568	54.2899	13.1363	13.2831	13.4364
	3	84	79	65	40.6867	41.8543	40.0042	15.9418	15.6960	16.0887
	4	141	128	125	31.6291	32.1652	31.4545	18.1291	17.9831	18.1771
	5	193	203	188	23.4226	23.9251	22.1678	20.7381	20.5537	21.2164
Butterfly	2	56	44	59	71.4867	70.4563	69.8294	11.0463	11.1724	11.2500
	3	77	80	63	51.5077	52.0365	50.8355	13.8934	13.8046	14.0075
	4	109	117	93	36.4087	36.0466	35.8369	16.9067	16.9935	17.0442
	5	173	192	168	27.4835	27.7026	26.5802	19.3494	19.2804	19.6396

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