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Optimal Multilevel Image Thresholding: An Analysis with PSO and BFO Algorithms

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ABSTRACT

Multilevel thresholding is widely adopted in image processing and pattern recognition fields. In this paper, Otsu based bi–level and multi-level image segmentation problem is addressed using Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization (BFO) algorithms. Optimal thresholds are attained by analyzing histogram of the test image. Maximization of Otsu's between class variance function is adopted to guide the heuristic algorithm based exploration. Performance of the proposed method is tested on eight benchmark test images using various numbers of thresholds. An assessment between PSO (constant weight), PSO (varying weight), Adaptive BFO, and Enhanced BFO are performed and the experimental results are validated using well known statistical parameters. For a bi-level optimization problem, considered heuristic algorithms show equal performance. For increase in threshold levels, PSO (constant weight) offers faster convergence and Enhanced BFO provides better structural similarity (SSIM) index.

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INTRODUCTION

In imaging science, thresholding is adopted as a vital tool for image segmentation. Normally, in an image, gray ranks belonging to the objects are considerably dissimilar from the gray ranks of the background and segmentation process looks for grouping the pixels surrounded by significant regions. Hence, thresholding can be used to separate objects from background, and to provide selective partition between objects which have distinct gray ranks (Cuevas *et al*., 2010).

Finding the accurate threshold value to separate an image into desirable object and background remains an extremely significant step in imaging science. Several thresholding procedures have been proposed and implemented by most of the researchers. Detailed reviews on existing thresholding techniques can be found in the literature (Lee *et al*., 1990; Pal and Pal, 1993; Sezgin and Sankar, 2004). Among them, global thresholding is considered as the most preferred image segmentation technique because of its simplicity, robustness, accuracy, and competence (Agrawal *et al*., 2013).

Based on the segmentation method, global thresholding is categorized as parametric and nonparametric technique. In existing parametric thresholding procedures, the statistical parameters of the image are estimated using standard strategies. Hence, this approach is computationally expensive, time consuming, and some times the performance degrades based on image quality. The nonparametric traditional approaches such as Otsu, Kapur, Tsai, and Kittler are uncomplicated and successful in bi-level thresholding (Nacereddine *et al*., 2007).

Traditional methods work well for a bi-level thresholding problem. When number of threshold level increases, complexity of thresholding problem also will increase and the traditional method require more computational time. Hence, in recent years, softcomputing algorithm based multi-level image thresholding procedure is widely proposed by the researchers. Heuristic algorithm based techniques such as Particle Swarm Optimization (PSO) (Manikantan *et al*., 2012; Raja *et al*., 2012; Sathya and Kayalvizhi, 2010; Maitra and Chatterjee, 2008), Bacterial Foraging Optimization (BFO) (Sathya and Kayalvizhi, 2011), Differential Evaluation (DE) (Sarkar *et al*., 2012; Su and Hu, 2013; Sarkar and Das, 2013), Artificial Bee Colony (ABC) (Horng, 2011; Akay, 2013), Cuckoo Search (CS) (Panda *et al*., 2013) are widely considered in optimal multilevel image segmentation problem, to enhance the final outcome. Recently, Hammouche *et al*. (2010) discussed about Genetic Algorithm, PSO, DE, Ant Colony Optimization (ACO), Simulated Annealing and Tabu search technique based multilevel image thresholding and concluded that PSO offers greater search speed compared to other methods.

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Detailed reviews on existing heuristic and metaheuristic algorithms available have been discussed by Bahesti and Shamsuddin (2013). Previous studies in the literature substantiate that, nature inspired heuristic algorithms such as PSO and BFO successfully established its ability in variety of engineering optimization problems. The classical and enhanced version of PSO algorithm could be found in (Kennedy and Eberhart, 1995; Zhao and Suganthan, 2011; Qu *et al*., 2012) and the traditional and modified form of BFO is available in the following articles (Passino, 2002; Dasgupta *et al*., 2009; Chen *et al*., 2011; Rajinikanth and Latha, 2012).

In the present work, multilevel image thresholding problem is addressed using existing PSO and BFO algorithms. Performance of the proposed technique is tested on eight standard test images and a comparative analysis is presented between the PSO (constant weight), PSO (varying weight), Adaptive BFO, and Enhanced BFO algorithms.

Otsu Based Multilevel Thresholding:

Otsu based image thresholding is initially proposed in the year 1979 (Otsu, 1979). The research findings by Sathya and Kayalvizhi shows that, Otsu offers better separation between the object and background compared to Kapur's method (Sathya and Kayalvizhi, 2010; 2011). In this work, Otsu's nonparametric segmentation method known as between-class variance is considered. This method finds the optimal threshold values of test image by maximizing the objective function. A detailed description of the between-class variance method is broadly addressed by several researchers (Hamed, 2012).

In Otsu's bi-level thresholding technique, input image is divided into two classes such as C_0 and C_1 (background and objects) by a threshold at a level 't'. As depicted in Fig 1, 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.

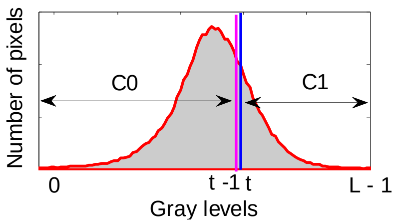

Fig. 1: Graphical representation of bi-level thresholding

The probability distributions for the gray levels C_0 and C_1 can be expressed as;

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

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

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

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

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;

$$Maximize\ J(t) = \sigma_0 + \sigma_1 \tag{3}$$

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 multilevel 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;

$$Maximize\ J(t) = \sigma_0 + \sigma_1 + \ldots + \sigma_m \tag{4}$$

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

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

Heuristic Algorithms:

In the past decades, heuristic algorithms are emerged as a powerful tool in solving a class of constrained and unconstrained optimization tasks. Literature evident that, PSO and BFO algorithms are successfully implemented in variety of engineering optimization problems. In this paper, PSO and BFO algorithms are adopted.

- PSO is an evolutionary kind global optimization technique, developed due to the inspiration of the social activities in flock of birds and school of fish, and widely adopted by the researchers because of its high computational efficiency. In PSO algorithm, the number of initial parameters to be assigned is very few compared to other nature inspired algorithms. In this work, the following two classes of PSO algorithms are considered;

(a) PSO - varying weight:

PSO with adaptive weight strategy has the following key parameters (Rajinikanth and Latha, 2013);

Velocity update = $V_k^{T+1} = W^T.V_k^T + C_1.R_1.(P_k^T - S_k^T) + C_2.R_2.(G_k^T - S_k^T)$ (5)

Position update = $S_k^{T+1} = S_k^T + V_k^{K+1}$ (6)

Weight update = $W^T = W_{max} - \left(Iter \;\; x \left[\frac{(W_{max} - W_{min})}{Iter_{max}} \right] \right)$ (7)

where W^T – inertia weight, V_k^T - current velocity of particle, V_k^{T+1} - updated velocity of particle, S_k^T - current position of particle, S_k^{T+1} - updated position of particle, R1, R2 are the random numbers in the range 0 − 1, C1 = C2 = 2.1 is the cognitive and global learning rate respectively, W_{max} – 0.9, W_{min} – 0.5, iter – current iteration number, $iter_{max}$ – maximum iteration number (in this work $iter_{max}$ = 250). The bird size and bird step are assigned as 20.

(b) PSO-constant weight (PSO1):

Recent study by Latha *et al*. (2012a) reported that, PSO with constant inertia weight offers improved speed in algorithm convergence by maintaining good accuracy in optimized parameters for PID controller design problem (Agalya and Nagaraj, 2013; Kotteeswaran and Sivakumar, 2014; 2014a). In the proposed work, Eqn. (5) and (6) are adopted and the inertia weight (W^T) in is chosen as 0.75.

- BFO algorithm is a population based optimization technique developed by inspiring the foraging manners of E.coli bacteria (Passino, 2002). The main advantage of BFO algorithm is, it offers better result compared to other existing optimization methods. In this work, the following classes of BFO algorithms are considered.

(c) Adaptive BFO (ABFO):

This algorithm was proposed by Dasgupta *et al*. (2009) with the subsequent algorithm parameters: number of bacteria (N) = 20, number of chemotaxis step (N_c) = 20, swim length (N_s) = 12, number of elimination – dispersal events (N_{ed}) = 4, N_{re} (number of bacterial reproduction) =16, P_{ed} (probability of bacterial elimination/dispersal) = 0.25, $d_{attractant}$ = 0.1, $W_{attractant}$ = 0.2, $h_{repellant}$ =0.1, $W_{repellent}$ =10, and λ = 20.

(d) Enhanced BFO (EBFO):

EBFO is a modified form of classical BFO algorithm, proposed by Rajinikanth and Latha (2012). The initial algorithm parameters are assigned as follows;

Number of E.Coli bacteria = $10 < N < 30$ (in this work N = 20) ; $N_c = \frac{N}{2}$; $N_s = N_{re} \approx \frac{N}{3}$; $N_{ed} \approx \frac{N}{4}$; $N_r = \frac{N}{2}$; $P_{ed} = \left(\frac{N_{ed}}{N + N_r} \right)$;

$d_{attractant} = W_{attractant} = \frac{N_s}{N}$; *and* $h_{repellant} = W_{repellent} = \frac{N_c}{N}$.

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).

Implementation:

Multi-level thresholding problem discovers optimal thresholds within the gray scale range [0, L−1] that maximizes an objective function *J(t)*. In this work, optimal multi-level thresholding has been carried out by an unsupervised nonparametric approach known as Otsu's between class variance function. The search dimension (D) for the heuristic algorithm is assigned based on the considered threshold levels (m). In the proposed approach, the efficiencies of PSO, PSO1, ABFO and EBFO are tested separately, and their performances have been compared.

(a)Performance appraisal:

The performance of the Otsu guided heuristic algorithms are evaluated using the indices such as Peak-to-Signal Ratio (PSNR) and Structural Similarity Indices (SSIM) (Akay, 2013; Wang *et al*., 2004).

The PSNR is mathematically represented as;

$$PSNR(x,y) = 20 \log_{10}\left(\frac{255}{\sqrt{MSE(x,y)}}\right) \tag{8}$$

where MSE – Mean Square Error of each pixel.

The SSIM is normally used to estimate the image quality and inter dependencies between the original and processed image. SSIM index combines luminance comparison, contrast comparison and structure comparison and satisfies symmetry, boundedness and unique maximum properties.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + A_1)(2\sigma_{xy} + A_2)}{(\mu_x^2 + \mu_y^2 - A_1)(\sigma_{x^2} + \sigma_{y^2} + A_2)} \tag{9}$$

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, A_1= $(k_1L)^2$ and A_2= $(k_1L)^2$ stabilize the division with weak denominator, L = 256, k_1 = 0.01, and k_2 = 0.03 (Akay, 2013).

(b) Execution:

In heuristic algorithm based optimization practice, dimension of heuristic search varies from 2 to 5 depending on ‘m’ levels. When, m = 2, it is a simple two dimensional optimization problem and heuristic search may offer better result with lesser iterations. When ‘m’ increases, complexity of optimization problem also increases and the algorithm requires more computation time to offer the optimal threshold.

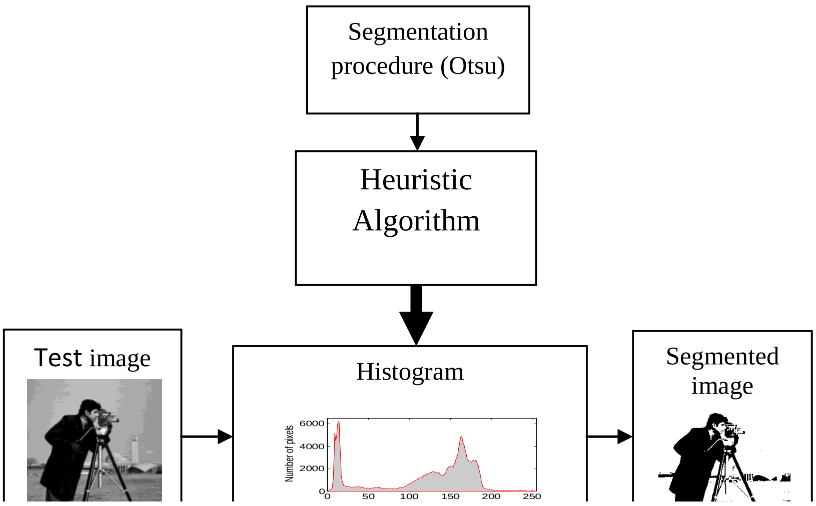

Fig. 2: Block diagram of heuristic algorithm based image segmentation scheme

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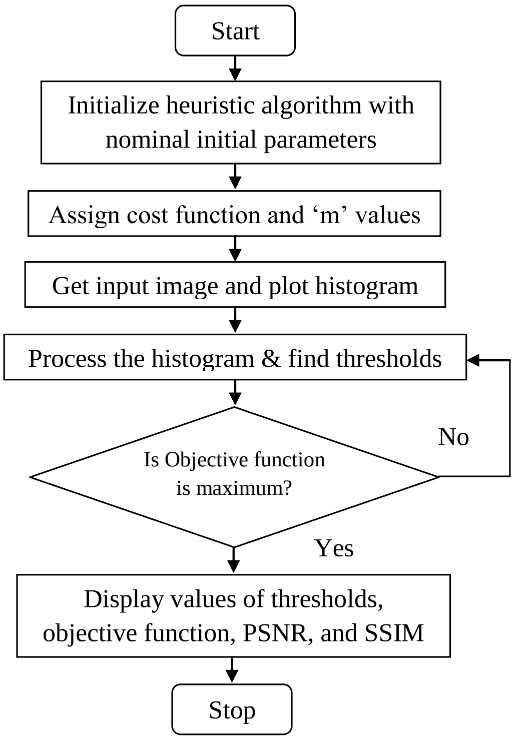


Fig. 3: Flow chart of proposed method

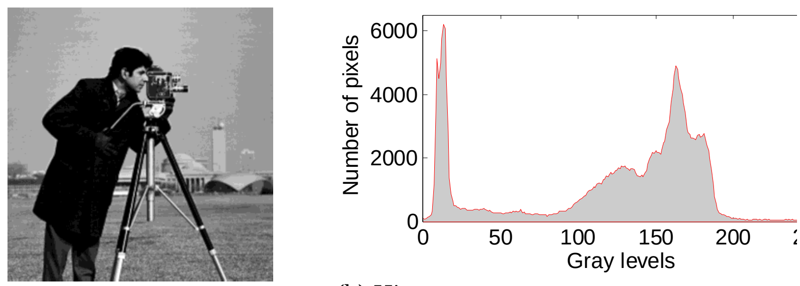
Fig. 2 shows the block diagram of heuristic algorithm based image segmentation scheme. Fig. 3 depicts the flow chart of the proposed work. The heuristic algorithm based search process is initialized with the necessary initial parameters such as population size, objective function, search dimension, and maximum iteration. The algorithm, initially analyze the histogram of the input image and finds the threshold levels arbitrarily based on the assigned guiding parameters. When the objective function is satisfied, the algorithm displays the essential parameters like Otsu's objective function, optimal threshold based on 'm', PSNR, and SSIM.

RESULTS AND DISCUSSIONS

In this work, heuristic algorithm based multi-level thresholding techniques have been applied firstly on standard 512 x 512 test images such as Cameraman, and Lena. Later, this procedure is executed on 481 x 321 sized test images such as Starfish, Farmer, Milkman, Leopard, Train, and Palace available in Berkeley Segmentation Dataset (Martin *et al*., 2001).

The experiment was 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, the population size of heuristic algorithm is assigned as 20 and the maximum iteration number is assigned as 250. Each image is examined with a number of thresholds varying m = 2 to 5 and the simulation study is repeated 10 times individually and best value among the search is recorded as optimal threshold value.

CAMERAMAN



(a) Original image (b) Histogram

Fig. 4: Cameraman image and its histogram

Fig. 4 (a) and (b) shows the cameraman image and its corresponding histogram. For a chosen 'm' value, image thresholding process is implemented on the cameraman image using PSO, PSO1, ABFO, and EBFO algorithms based on the procedure discussed in section 4.2. The convergence of heuristic algorithm based optimization search is presented in Fig. 5 for m = 2. The PSO based search is converged at 26th iteration, PSO1 converges at 17th iteration, ABFO converges at 22nd iteration and EBFO converges at 51st iteration for m=2. Information like final objective function, optimal threshold value, PSNR, and SSIM are presented in Table 1 and 2. From the table, it is noted that, even though the convergence time is large, EBFO algorithm offers better SSIM compared to other considered algorithms.

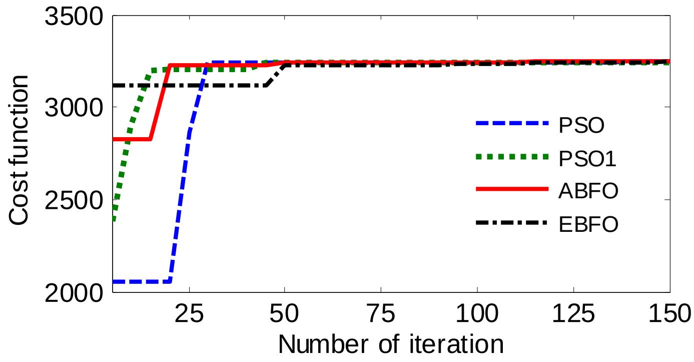
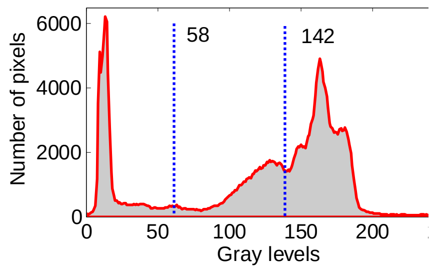
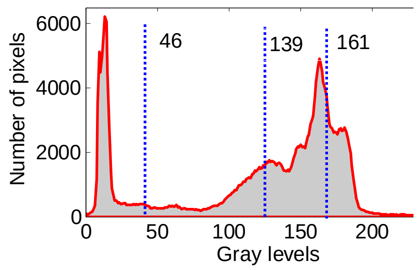


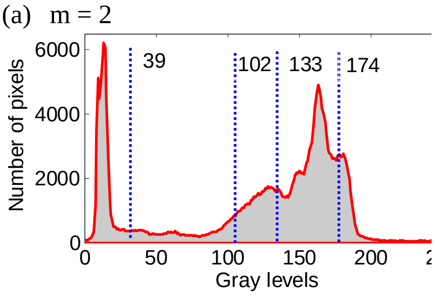
Fig . 5: Variation of objective function



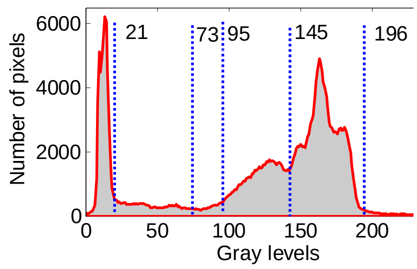
(a) m = 2



(b) m = 3



(c) m = 4



(d) m = 5

Fig. 6: Ditribution of optimal thresholds for various 'm' levels

Fig. 6 (a-d) depicts the distribution of the optimal threshold values on the gray level histogram of Cameraman image for m = 2-5 using EBFO. Similar results are obtained for PSO, PSO1, ABFO and the results are presented in Table 1 and 2. Fig. 7 (a-d) shows original image and histogram of Lena (512x512) and Starfish (481 x 321) image. Above discussed thresholding procedure is extended to these images and the results are tabulated in Table 1 and 2. The simulation result proves that the PSO1 offers optimal values with lesser iteration number compared to PSO, ABFO, and EBFO. Table 3 presents the segmented images of Cameraman, Lena, and Starfish for m = 2-5.

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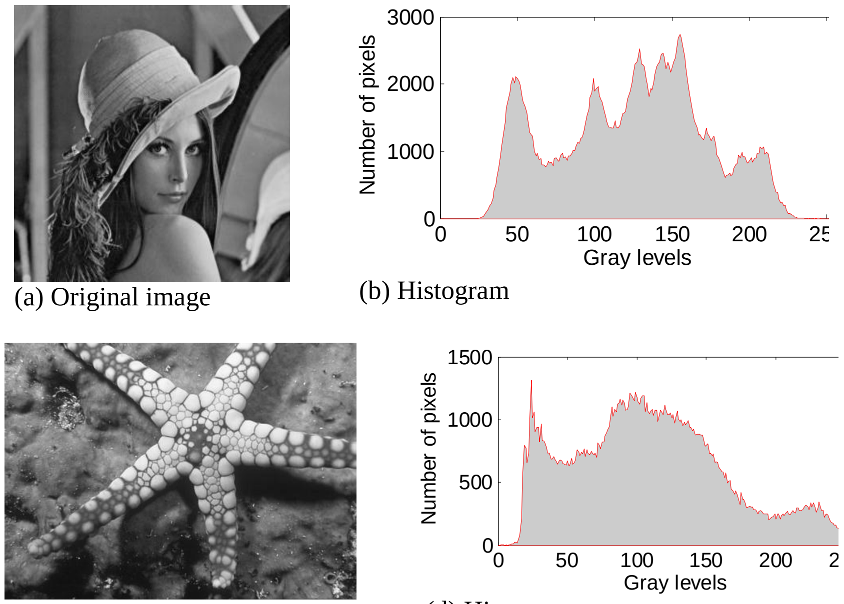
LENA

STARFISH



(a) Original image (b) Histogram

(c) Original image (d) Histogram

Fig. 7: Test image and corresponding histogram

Table 1: Optimal threshold values for Cameraman, Lena, and Starfish

Image	m	PSO	PSO1	ABFO	EBFO
CAMERA MAN	2	74, 148	66, 150	63, 146	58, 142
	3	58, 108, 162	52, 120, 164	52, 111, 166	46,139, 161
	4	52, 112, 138, 172	50, 110, 129, 176	48, 108, 141, 181	39, 102, 133, 174
	5	38, 76, 100,148,192	44, 78, 105,153,188	29, 93,120,148,196	21,73,95,145,196
LENA	2	68,148	72,152	72,150	78,147
	3	60,116,169	48,122,178	54,105,181	62,113,174
	4	47,88,132,176	52,95,142,181	50,103,149,183	54,97,146,180
	5	51,66,121,146,182	47,72,104,139,180	38,78,118,140,172	42,83,116,134,178
STAR FISH	2	62,152	64,150	68,154	64,152
	3	48,105,172	50,118,164	44,106,170	48,112,188
	4	53,110,136,184	56,106,138,188	52,116,141,182	50,120,151,186
	5	44,82,107,144,201	42,86,111,138,198	50,91,106,142,210	49,102,122,136,200

Table 2: Performance measure values for Cameraman, Lena, and Starfish

Image	m	Objective function				SSIM				PSNR (dB)			
		PSO	PSO1	ABFO	EBFO	PSO	PSO1	ABFO	EBFO	PSO	PSO1	ABFO	EBFO
CAMERAMAN	2	3238.54	3240.62	3244.15	3244.70	0.742	0.751	0.810	0.815	20.087	20.155	19.320	20.313
	3	3240.10	3241.00	3242.24	3242.31	0.747	0.759	0.768	0.817	22.117	21.845	22.472	24.046
	4	3241.32	3240.10	3241.54	3241.68	0.753	0.763	0.773	0.822	24.581	23.772	24.045	24.773
	5	3240.78	3241.12	3241.04	3242.10	0.804	0.809	0.818	0.824	25.048	25.160	26.172	25.905
LENA	2	1922.10	1920.44	1922.82	1922.63	0.680	0.688	0.786	0.790	20.942	21.021	22.180	22.227
	3	1923.04	1922.88	1923.14	1924.01	0.695	0.707	0.731	0.733	22.047	22.575	23.047	22.930
	4	1924.00	1924.41	1924.73	1924.80	0.653	0.732	0.716	0.806	23.577	24.009	25.291	25.805
	5	1924.11	1924.20	1924.52	1924.50	0.731	0.764	0.811	0.827	25.091	25.361	25.735	26.115
STARFISH	2	1983.17	1983.62	1983.88	1983.92	0.638	0.625	0.677	0.682	20.271	21.727	20.901	21.515
	3	1982.10	1983.08	1982.36	1984.27	0.642	0.650	0.681	0.704	21.904	22.823	23.101	23.227
	4	1983.48	1983.22	1983.92	1984.10	0.671	0.703	0.700	0.726	23.226	23.026	23.883	23.691
	5	1984.00	1984.20	1984.45	1984.62	0.694	0.727	0.708	0.733	24.073	24.518	24.733	24.771

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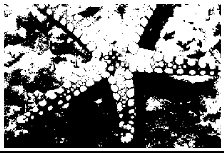
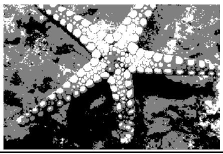
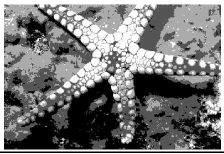
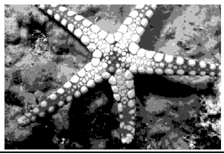
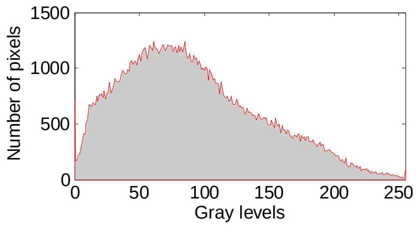
Table 3: Segmented image for various 'm' levels

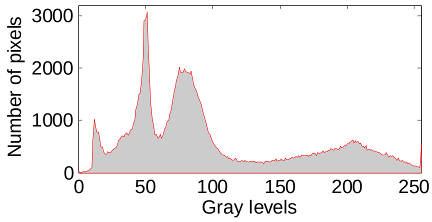
Image	m = 2	m = 3	m = 4	m = 5
CAMERAMAN				
LENA				
STARFISH				

(a) Farmer image



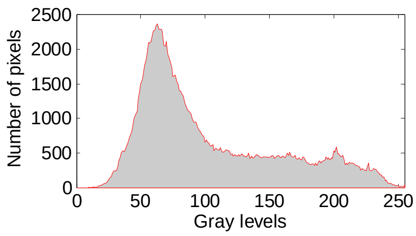
(b) Histogram

(c) Milkman image



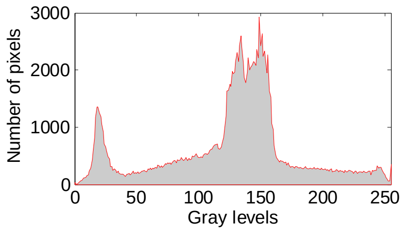
(d) Histogram

(e) Leopard image



(f) Histogram

(g) Train image



(h) Histogram

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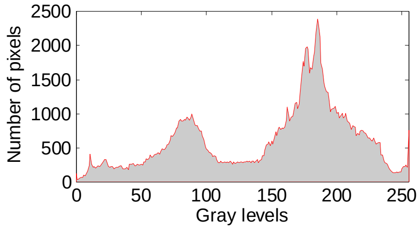
(i) Place image



(j) Histogram

Fig. 9: 481 x 321 sized test images (a, c, e, g, i) and the corresponding histogram (b, d, f, h, j)

Table 4: Bi-level and multi-level threshold images

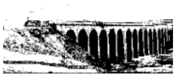
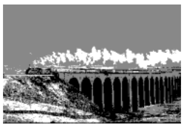
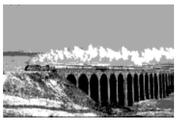
Image	m = 2	m = 3	m = 4	m = 5
Farmer				
Milkman				
Leopard				
Train				
Palace				

Table 5: Optimal threshold values for 481 x 321 sized test images

Image	m	PSO	PSO1	ABFO	EBFO
Farmer	2	54,138	49,142	55,140	52,142
	3	36,104,168	47,115,170	44,98,177	49,108,172
	4	44,92,133,185	39,75,129,180	51,86,133,188	42,69,115,173
	5	25,58,84,131,197	33,72,92,144,192	22,66,110,152,206	29,53,121,164,211
Milk man	2	48,132	46,138	40,146	48,152
	3	38,84,140	42,79,157	32,96,168	44,85,179
	4	22,72,114,195	28,68,124,176	34,88,132,210	20,94,163,218
	5	20,62,83,128,200	24,70,94,118,196	20,78,112,182,225	27,48,106,172,208
Leopard	2	88,132	84,136	88,140	82,144
	3	48,110,154	52,123,162	46,138,169	42,136,178
	4	42,68,132,198	44,72,118,186	50,84,144,211	48,78,126,208
	5	44,72,98,142,210	40,66,103,138,204	47,81,94,133,196	40,78,114,168,202
Train	2	98, 188	94, 185	94, 182	98, 180
	3	44,146,204	38,139,196	40,142,188	38,154,179
	4	35,122,146,190	38,131,150,194	42,128,153,208	36,133,148,224
	5	30,66,117,136,207	37,74,122,149,232	34,93,142,158,196	28,84,127,151,206
Palace	2	76,128	72,130	74,122	70,118
	3	44,156,214	56,171,204	62,162,188	51.174,190
	4	24,59,162,202	33,80,144,188	30,92,166,207	42,115,174,191
	5	20,48,78,159,210	26,62,95,130,192	32,59,94,158,223	48,74,168,182,216

Table 6: Performance measure values for 481 x 321 sized test images

Image	m	Cost function				SSIM				PSNR (dB)			
		PSO	PSO1	ABFO	EBFO	PSO	PSO1	ABFO	EBFO	PSO	PSO1	ABFO	EBFO
Farmer	2	1911.99	1912.04	1912.00	1912.46	0.781	0.766	0.809	0.820	18.002	17.805	18.193	18.027
	3	1912.12	1912.52	1912.71	1913.05	0.763	0.793	0.825	0.829	19.773	20.284	20.063	22.731
	4	1913.01	1912.99	1913.08	1913.40	0.803	0.794	0.832	0.850	22.921	22.016	23.701	23.833
	5	1913.12	1913.88	1913.21	1913.62	0.821	0.817	0.826	0.882	23.542	23.024	24.014	24.122
Milk man	2	3314.62	3314.35	3314.60	3314.99	0.764	0.727	0.798	0.808	17.002	18.153	20.015	20.644
	3	3316.38	3316.10	3316.72	3316.85	0.792	0.784	0.825	0.852	19.252	19.384	22.103	22.462
	4	3316.08	3316.51	3317.01	3317.92	0.824	0.829	0.862	0.867	19.835	20.218	22.571	23.116
	5	3318.07	3317.88	3318.12	3318.73	0.829	0.833	0.870	0.888	21.931	22.723	22.893	23.203
Leopard	2	2342.07	2342.91	2342.92	2342.99	0.726	0.718	0.752	0.793	16.734	15.377	17.582	17.032
	3	2343.62	2342.84	2342.66	2343.81	0.785	0.799	0.815	0.822	18.117	16.020	17.925	17.378
	4	2345.22	2344.89	2344.90	2345.77	0.813	0.826	0.855	0.859	18.261	17.000	18.043	18.318
	5	2346.06	2346.41	2346.35	2346.54	0.828	0.831	0.858	0.869	18.545	17.133	18.205	18.491
Train	2	1827.57	1828.05	1828.33	1828.90	0.725	0.753	0.760	0.761	16.309	15.972	17.211	16.661
	3	1828.84	1828.55	1829.15	1829.27	0.773	0.768	0.792	0.800	17.035	16.035	17.491	17.002
	4	1829.62	1829.48	1830.12	1830.48	0.796	0.788	0.803	0.817	17.502	16.172	17.937	17.316
	5	1830.41	1830.27	1830.68	1831.01	0.804	0.823	0.811	0.831	18.063	18.428	19.026	19.100
Palace	2	2823.26	2823.72	2823.52	2823.96	0.781	0.755	0.763	0.780	18.172	19.321	19.530	19.472
	3	2824.04	2823.84	2824.11	2824.57	0.803	0.821	0.830	0.827	21.035	20.016	21.583	21.804
	4	2826.66	2826.24	2827.18	2827.36	0.816	0.825	0.832	0.841	22.811	21.192	22.741	23.000
	5	2828.12	2828.51	2828.46	2828.74	0.833	0.848	0.855	0.870	24.088	23.184	24.193	24.117

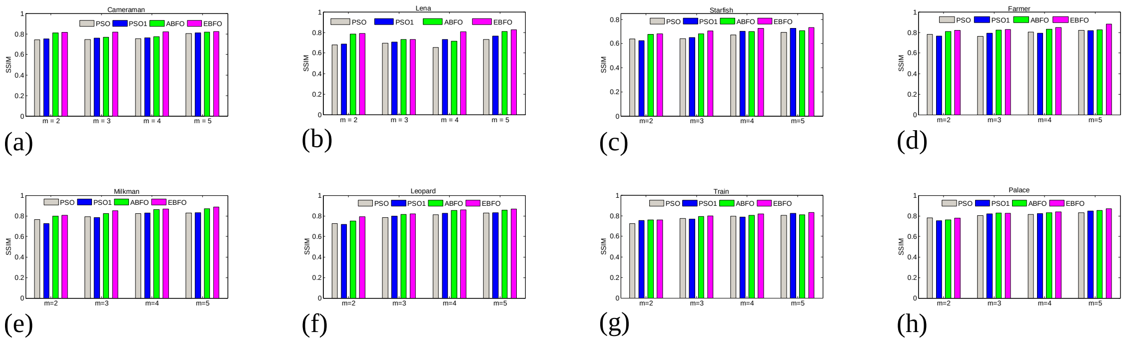


Fig. 10: Comparison of SSIM for various 'm' levels

To analyze the performance of considered heuristic algorithms, five 481 x 321 sized test images are taken from the Berkeley segmentation dataset (Martin *ET AL*., 2001) and analyzed using bi-level and multi-level thresholds. Fig. 9 depicts the considered test images and its histogram level. These images are analyzed using PSO, PSO1, ABFO, EBFO as per the procedure discussed in implementation section and the results are tabulated in Table 4, 5, and 6. The performance of the considered heuristic algorithms is assed using the image parameters such as PSNR and SSIM. Comparison of attained SSIM for the test images with various threshold levels are presented in Fig. 10. From this, it is noted that, SSIM obtained with the EBFO algorithm is better compared to PSO, PSO1, and ABFO for both the bi-level and multi-level thresholds.

Conclusion:

In this study, optimal bi-level and multi-level image thresholding problem is discussed using PSO (constant weight), PSO (varying weight), Adaptive BFO, and Enhanced BFO algorithms. Maximization of Otsu's between class variance is chosen as the objective function. 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. Experimental results demonstrates that, PSO (constant weight) converges earlier compared to PSO (varying weight), ABFO, and EBFO algorithm. Even though the convergence time is large, the EBFO based method offers better SSIM compared to other algorithms. The future work will include a bounded threshold search in order to improve the convergence time, and implementation of multi-objective criteria for both the bi-level and multi-level image thresholding.

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