



## Solving Image Thresholding Problem using Hybrid Algorithm

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### ABSTRACT

Thresholding is a reputed image segmentation technique used to obtain binary image from the gray level image. In this paper, histogram based bi-level and multi-level segmentation is proposed using Improved Particle Swarm Optimization (PSO) and Enhanced Bacterial Foraging Optimization (EBFO) based hybrid algorithm. The optimal thresholds for input images are attained by maximizing Otsu's between class variance function. The performance of proposed method is demonstrated on four benchmark images and compared with the existing PSO and BFO algorithms. An assessment between HA, PSO, and BFO is carried using prevailing parameters such as objective function, convergence rate, PSNR, and DSSIM.

**Keywords:** *Otsu; Hybrid algorithm; Segmentation*

### 1. Introduction

In imaging science, image processing plays a vital role in the analysis and interpretation of images in fields such as medical discipline, navigation, environment modelling, automatic event detection, surveillance, texture and pattern recognition, and damage detection. The development of digital imaging techniques and computing technology increased the potential of imaging science.

Image segmentation is one of pre-processing technique widely employed in imaging science to extract key features from input image. Segmentation is judged as an important procedure for significant examination and interpretation of images.

In the literature, many segmentation procedures have

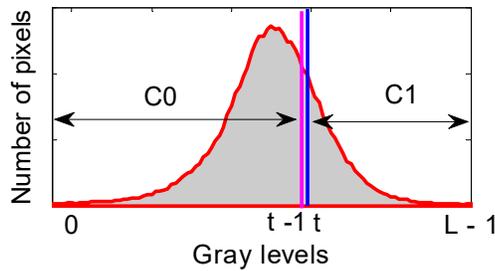
been proposed and implemented by most of the researchers [1-3]. Among them, global thresholding is considered as the most efficient procedure for image segmentation, because of its simplicity, robustness, accuracy and competence [4]. Based on the segmentation method, global thresholding is categorized 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 the image quality [5, 6]. The nonparametric traditional approaches such as Otsu, Kapur, Tsai, and Kittler are uncomplicated and successful in bi-level thresholding.

Traditional methods work well for a bi-level thresholding problem, when the number of threshold level increases, complexity of the thresholding problem also will increase and the traditional method requires more computational time. Hence, in recent years, softcomputing algorithm based multi-level image thresholding procedure is widely proposed by the researchers [7-9].

In this work, a novel hybrid algorithm is proposed to solve the image thresholding problem by maximising Otsu's between-class variance function. The proposed technique is tested on four standard test images and compared with the Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization (BFO) based image segmentation techniques.

### 2. Methodology

Otsu based image thresholding is initially proposed in the year 1979 [10]. The research findings by Sathya and Kayalvizhi shows that, Otsu offers better separation between the object and background compared to Kapur’s method [4, 9]. 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. 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.



**Figure 1 Graphical representation of bi-level thresholding**

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

$$C_0 = \frac{P_0}{\omega_0(t)} \dots \frac{P_{t-1}}{\omega_0(t)} \quad \text{and}$$

$$C_1 = \frac{P_t}{\omega_1(t)} \dots \frac{P_{L-1}}{\omega_1(t)} \quad (1)$$

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  $\mu_0$  and  $\mu_1$  for  $C_0$  and  $C_1$  can be expressed as;

$$\mu_0 = \sum_{i=0}^{t-1} \frac{ip_i}{\omega_0(t)} \quad \text{and} \quad \mu_1 = \sum_{i=t}^{L-1} \frac{ip_i}{\omega_1(t)} \quad (2)$$

The mean intensity ( $\mu_T$ ) of the entire image can be represented as;

$$\mu_T = \omega_0\mu_0 + \omega_1\mu_1 \quad \text{and} \quad \omega_0 + \omega_1 = 1$$

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

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

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 ( $t_1, t_2, \dots, t_m$ ), which divide the input image into ‘m’ classes:  $C_0$  with gray levels in the range 0 to  $t_1-1$ ,  $C_1$  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;

$$\text{Maximize } J(t) = \sigma_0 + \sigma_1 + \dots + \sigma_m \quad (4)$$

Where  $\sigma_0 = \omega_0(\mu_0 - \mu_T)^2, \sigma_1 = \omega_1(\mu_1 - \mu_T)^2, \dots, \sigma_m = \omega_m(\mu_m - \mu_T)^2$ .

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

### 3. Hybrid Algorithm

The limitations of a particular optimization algorithm can be minimized with hybridization techniques. Recently a class of hybridization techniques are proposed and implemented for a class of engineering optimization problems. The hybrid algorithm is formed by combining two existing evolutionary optimization algorithms.

**(a) PSO-constant weight (PSO1):** Recent study by Latha et al. 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 [11, 12]. In the proposed work, Eqn. (5) and (6) are adopted and the inertia weight ( $W^T$ ) in is chosen as 0.75.

**(b) Enhanced BFO (EBFO):** EBFO is a modified form of classical BFO algorithm, proposed by Rajinikanth and Latha [13]. The initial algorithm parameters are assigned as follows;

Number of E.Coli bacteria =  $10 < N < 30$  ;

$$N_c = \frac{N}{2} ; N_s = N_{re} \approx 3 ; N_{ed} \approx 4 ; N_r = \frac{N}{2}$$

$$P_{ed} = \left( \frac{N_{ed}}{N + N_r} \right); d_{attractant} = W_{attractant} = \frac{N_s}{N}; \quad \text{and}$$

$$h_{repellant} = W_{repellant} = \frac{N_c}{N}.$$

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).

In this research work, we combined the existing PSO algorithm with EBFO, in order to increase the search speed and optimization accuracy. The PSO+BFO based hybrid method is initially proposed by Wael et al (2008) to improve the performance of classical BFO algorithm [14].

In this, the Objective Function (OF) is applied for both the PSO and EBFO algorithm. The PSO algorithm monitors the EBFO to achieve a minimum convergence time with optimized parameters. In hybrid algorithm, after undergoing a chemo tactic step, each bacterium gets mutated by a PSO operator.

During this operation, the bacterium is stochastically attracted towards the global best position obtained so far in the entire population. The PSO operator uses only the social component and eliminates the cognitive component to support the local search. The velocity operator of PSO is used to activate the tumble operator of EBFO. In this algorithm, due to the information sharing between the PSO and EBFO, better optimized solutions are obtained with minimal convergence time compared to a conventional BFO algorithm.

#### 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.

The performance of the hybrid algorithm is assessed using the well known parameters such as peak-to-signal ratio (PSNR) and structural similarity indices (SSIM)

[15].

The PSNR is mathematically represented as;

$$PSNR(x, y) = 20 \log_{10} \left( \frac{255}{\sqrt{MSE(x, y)}} \right) \quad (9)$$

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

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 - C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (10)$$

Where  $\mu_x$  = average of x,  $\mu_y$  = average of y,  $\sigma_x^2$  = variance of x,  $\sigma_y^2$  = variance of y,  $\sigma_{xy}$  = covariance of x and y,  $C_1 = (k_1L)^2$  and  $C_2 = (k_2L)^2$  stabilize the division with weak denominator,  $L = 256$ ,  $k_1 = 0.01$ , and  $k_2 = 0.03$ .

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.

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.

#### 5. Results and Discussion

Otsu guided multi-level thresholding techniques have been initially tested on standard 512 x 512 test images such as Lena, Lake, Car, and Pirate from the image database existing in the literature. In this paper, a proposal is made to find the optimal multilevel thresholds for the above said images using a novel hybrid algorithm.

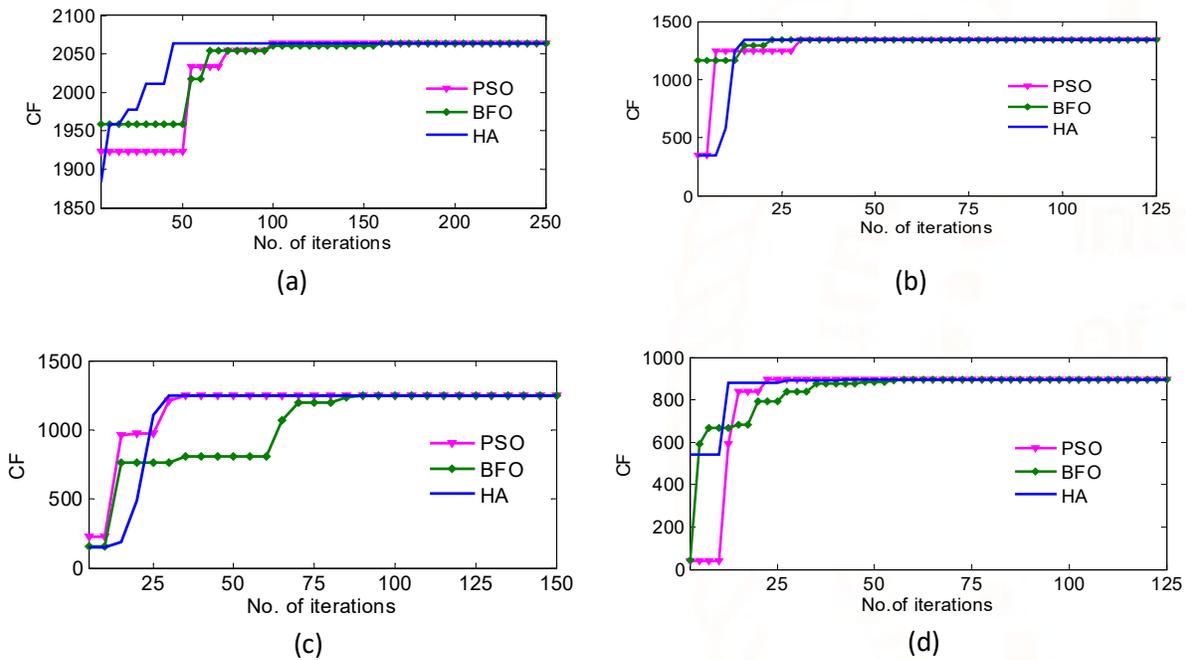
The PSO parameters are assigned as discussed in [12] and the BFO parameters are assigned as discussed in [13]; the total number of run is chosen as 300. During the experiment, each image is examined with a number of thresholds such as  $m = 2$  to 5. The simulation study is repeated 10 times individually and

the best value among the search is recorded as the optimal threshold value.

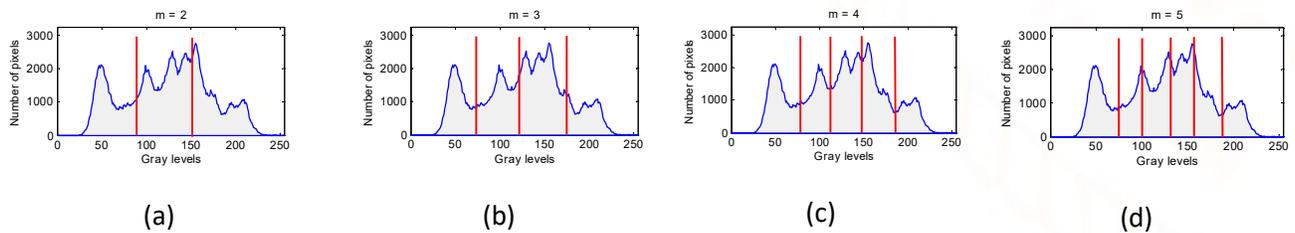
Initially, the proposed method is tested on the Lena image. Fig .2 (a) shows the convergence of the search with PSO, BFO and HA for  $m=2$ . Where, HA converged at 33th iteration, PSO and BFO converges at 78th and 82nd iterations respectively. From this, it is observed that, hybrid algorithm converges fast compared to the considered PSO and BFO algorithm. Similar results are obtained for other considered images as depicted in Fig .2 (b) to (d).

Fig. 3 (a) – (d) represents the segmented histogram of the Lena image for  $m= 2$  to 5. Table 1 represents the original test image, histogram, and segmented image for various ‘m’ values.

Table 2 depicts various performance measure values obtained during the image segmentation process. For smaller threshold values ( $m=2$  and 3), the proposed algorithm shows better PSNR and SSIM value. For higher threshold values ( $m=4$  and 5), the proposed algorithm provides a satisfactory PSNR and SSIM.



**Figure 2. Convergence of cost function for PSO, BFO, and hybrid algorithm**



**Figure 3. Optimal threshold level for Lena image for  $m = 2$  to 5**

Image	m	Optimal threshold	OF	Iteration	PSNR	SSIM
Lena	2	85, 105	1919.78	33	17.502	0.781
	3	65, 109, 173	1919.99	78	18.063	0.763
	4	76, 111, 148, 196	1921.25	120	18.172	0.803
	5	67, 96, 132, 166, 198	1923.44	133	21.035	0.821
Lake	2	93, 122	3473.46	37	17.002	0.725
	3	46, 118, 212	3474.15	62	19.252	0.773
	4	101, 117, 126, 136	3477.46	146	19.835	0.796
	5	81, 89, 117, 124, 133	3476.55	172	21.931	0.804
Car	2	134, 206	1583.06	62	18.193	0.809
	3	144, 148, 199	1583.05	71	20.063	0.825
	4	114, 140, 142, 161	1583.00	88	23.701	0.832
	5	108, 136, 139, 141, 226	1583.06	129	24.014	0.826
Pirate	2	124, 138	2063.55	48	19.530	0.752
	3	42, 125, 180	2067.24	81	21.583	0.815
	4	90, 106, 135, 158	2067.58	99	22.741	0.855
	5	113, 116, 124, 138, 146	2068.02	131	24.193	0.858

**Table 2. Performance measure values obtained for various test images**

## 6. Conclusion

In this paper, optimal multi-level image thresholding problem is addressed using Otsu guided hybrid algorithm. The performance of the proposed method is validated using four standard images. 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 increase in threshold levels. The convergence of proposed algorithm is better compared to the considered PSO and BFO algorithm for various 'm' levels.

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