Optimal Multilevel Image Threshold Selection Using a Novel Objective Function

V. Rajinikanth and M.S. Couceiro

Abstract Image thresholding is a reputed image segmentation process, extensively used to attain a binary image from a grey scale image. In this article, a bi-level and multi-level image segmentation approach is proposed for grey scale images using Bat Algorithm (BA). In this work, two novel Objective Functions (OF) are considered to obtain the optimal threshold values. The proposed segmentation process is demonstrated using six standard grey scale test images. The performance of the proposed OF-based segmentation procedure is validated using the traditional Otsu's between-class variance. The performance assessment between the proposed and existing OF is measured using well-known parameters, such as objective value, Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Matrix (SSIM) and CPU time. Results of this study show that the proposed OF provides a better objective value, PSNR and SSIM, whereas the existing OF offers faster convergence with a relatively lower CPU time.

Keywords Bat algorithm · Otsu · Between-class variance · PSNR · SSIM

1 Introduction

Image segmentation is one of pre-processing method used to adjust the features of an image. It is also considered as an important practice for significant analysis and interpretation of input images [1, 2].

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J.K. Mandal et al. (eds.), *Information Systems Design and Intelligent Applications*,
Advances in Intelligent Systems and Computing 340,
DOI 10.1007/978-81-322-2247-7_19

In the literature, a considerable number of image segmentation methods have been proposed and implemented by most of the researchers [3–5]. Among them, global thresholding is believed as the most chosen image segmentation process because of its simplicity, exactness, and competence [5]. The existing parametric thresholding approach is computationally costly, time consuming, and some cases the performance degrades depending on the image quality [6]. Nonparametric traditional methods, such as Otsu, Kapur, Tsai, and Kittler are simpler and effective for bi-level thresholding [7]. However, as the number of threshold level increases, the complexity of the segmentation problem also will increase and the conventional method requires more computational time. Therefore, to overcome the computational complexity in most of conventional methods, heuristic algorithm based bi-level and multi-level image thresholding procedures have been widely proposed by the researchers [6, 7].

In this paper, the Bat Algorithm (BA) proposed by Yang is considered [8]. The algorithm explores the 'm' dimensional search universe until the Objective Function (OF) reaches a maximal value. The proposed technique is tested on five standard 481 × 321 sized test images and the performance of the proposed and existing OF are validated using image parameters, such as objective value, Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Matrix (SSIM) and CPU time.

2 Brief Overview of Bat Algorithm

The Bat Algorithm (BA) is based on the echo location or bio-sonar characteristics of microbats. BA was developed by modelling the navigating and hunting abilities of bats [9]. A detailed investigation of the BA algorithm can be found in [1, 8, 10, 11].

The classical BA has three mathematical discrete equations, defining the velocity update (Eq. 1), the position update (Eq. 2), and the frequency vector (Eq. 3) as given below:

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

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{2}$$

$$F_i = F_{min} + (F_{max} - F_{min})\beta \tag{3}$$

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

From Eq. (1), it is observed that the velocity update primarily relies on the frequency vector. During the optimization search, a new solution for each bat is generated based on the following relation:

$$X_{new} = X_{old} + \varepsilon A^t \tag{4}$$

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 $A_0 = 20$, and $A_{min} = 1$ (which decay in steps of 0.05). Other related mathematical representations for loudness adjustment are presented below:

$$A_i(t+1) = \alpha A_i(t) \tag{5}$$

$$r_i(t+1) = r_i(0)[1 - \exp(-\gamma t)] \tag{6}$$

where α and γ are constants typically assigned with a numeral value of 0.75 [9].

3 Otsu Based Segmentation

Otsu's based image thresholding was initially proposed back in 1979 [12]. This method returns the optimal threshold of a given image by maximizing the between-class variance function. This procedure already proved its efficiency on grey scale [2, 13, 14] and colour images [15, 16].

3.1 Between-Class Variance

A detailed description of Otsu's between-class variance method can be found in [13, 15–17]. One can formalize the heuristic based segmentation procedure as follows:

For a given image, let there be L intensity levels in the range [0, 1, 2, …, $L - 1$]. In bi-level thresholding, 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 cluster C_0 encloses the grey plane in the range 0 to $t - 1$ and the cluster C_1 encloses the grey plane from t to $L - 1$.

The probability distributions for the grey planes C_0 and C_1 can be expressed as [12, 14]:

$$C_0 = \frac{p_0}{\omega_0(t)} \cdots \frac{p_{t-1}}{\omega_0(t)} \quad \text{and} \quad C_1 = \frac{p_t}{\omega_1(t)} \cdots \frac{p_{L-1}}{\omega 1(t)} \tag{7}$$

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

Note that p_i represents the probability distribution of intensity i within a given image. The mean levels μ_0 and μ_1 for C_0 and C_1 can be expressed as:

$$\mu_0 = \sum_{i=0}^{t-1} \frac{ip_i}{\omega_0(t)} \quad \text{and} \quad \mu_1 = \sum_{i=t}^{L-1} \frac{ip_i}{\omega 1(t)} \tag{8}$$

The mean intensity (μ_T) of the complete image can be characterized as

$$\mu_{\mathrm{T}} = \omega_0\mu_0 + \omega_1\mu_1 \quad \text{and} \quad \omega_0 + \omega_1 = 1$$

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

$$Maximize\ J(t) = \sigma_0 + \sigma_1 \tag{9}$$

where $\sigma_0 = \omega_0(\mu_0 - \mu_T)^2$ and $\sigma_1 = \omega_1(\mu_1 - \mu_{\mathrm{T}})^2$.

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

Let us consider there are 'm' thresholds (t_1, t_2, …, t_m), which divide the input image into 'm' classes: C_0 with grey levels in the range 0 to $t - 1$, C_1 with enclosed grey levels in the range t_1 to $t_2 - 1$, …, and C_m includes grey levels from t_m to $L - 1$.

Then, the objective function for the multi-level thresholding problem can be written as:

$$j_{max}(t) = \sigma_0 + \sigma_1 + \cdots + \sigma_m \tag{10}$$

where $\sigma_0 = \omega_0(\mu_0 - \mu_T)^2$, $\sigma_1 = \omega_1(\mu_1 - \mu_T)^2$, …, $\sigma_m = \omega_m(\mu_m - \mu_T)^2$, and $J_{max}(t)$ represents Otsu's between class variance function.

3.2 Performance Measurements

In the field of image processing, the quality of the segmented image is evaluated using universal image metrics, such as the Root Mean Squared Error (RMSE), the Standard deviation, the Peak Signal-to-Noise Ratio (PSNR), the Structural Similarity Index Matrix (SSIM), and the Structural Dissimilarity Index Matrix (SSIM). In addition to these metrics, auxiliary parameters, such as the final objective function value obtained (J_{max}), the number of iterations and the CPU processing time are also considered during the heuristic-based nonparametric optimization process.

In the proposed work, we considered J_{max}, PSNR, SSIM, and CPU time [2, 7]. Given that both J_{max} and CPU time are performance measures directly retrieved from the final outcome of the method without any auxiliary processing, PSNR and SSIM are briefly described below.

- PSNR is used to find the similarity of the segmented image against the original image based on the Root Mean Square Error (RMSE) of each pixel [2]:

$$PSNR(o,s) = 20\log_{10}\left(\frac{255}{\sqrt{MSE(o,s)}}\right);\ \text{dB} \tag{11}$$

$$RMSE_{(o,s)} = \sqrt{MSE_{(x,y)}} = \sqrt{\frac{1}{MN}\sum_{i=1}^{H}\sum_{j=1}^{W}[o(i,j) - s(i,j)]^2} \tag{12}$$

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

- SSIM is generally used to estimate the image superiority and inter-dependencies between the original and the processed image [2].

$$SSIM_{(o,s)} = \frac{(2\mu_o\mu_s + C_1)(2\sigma_{os} + C_2)}{(\mu_o^2 + \mu_s^2 - C_1)(\sigma_{o^2} + \sigma_{s^2} + C_2)} \tag{13}$$

where μ_o and μ_s are the average of o and s, σ_o^2 and σ_s^2 are the variance of o and s, σ_{os} is the covariance of o and s, and $C_1 = (k_1L)^2$ and $C_2 = (k_1L)^2$ stabilize the division with weak denominator, with $L = 256$, $k_1 = 0.01$, and $k_2 = 0.03$.

3.3 Objective Function

The segmentation process is initially accomplished using the existing Objective Function (OF) shown in Eq. (14).

$$J_{max1} = J_{max}(t) \tag{14}$$

In the proposed work, two weighted sum of multiple objective functions are proposed as presented in Eqs. (15) and (16).

$$J_{max2} = w1 \times J_{max}(t) + w2 \times \ \text{PSNR} \tag{15}$$

$$J_{max3} = w1 \times J_{max}(t) + w2 \times \text{PSNR} + w3 \times \text{SSIM} \tag{16}$$

where $w1$, $w2$, and $w3$ are weighting functions. The existing and the proposed objective functions are considered during the BA based optimal multi-level image segmentation process.

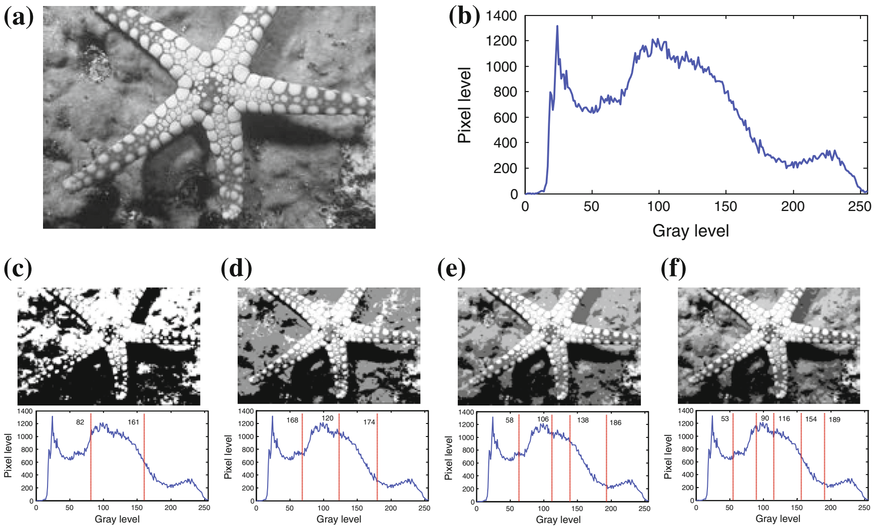


Fig. 1 Segmented Starfish image with J_{max3}. **a** Buttterfly image, **b** histogram, **c** m = 2, **d** m = 3, **e** m = 4, **f** m = 5

4 Result and Discussions

The proposed image segmentation experiment is implemented in Matlab R2010a on an AMD C70 Dual Core 1 GHz CPU, 4 GB RAM running Window 8. The proposed method is tested on standard grey scale (481 × 321 sized) dataset.[1] The number of thresholds (m) considered in this procedure are 2, 3, 4 and 5.

During the optimization search, population of bat is chosen as 20, number of iteration is allotted as 200, the search dimension is assigned as 'm', and the stopping criterion is J_{max}. For each image, and for each m, the segmentation procedure is repeated 20 times and the mean value among the trials is chosen as set of optimal thresholds and performance measures.

Initially the optimization procedure is tested on the Butterfly image for $m = \{2, 3, 4, 5\}$ using the existing and the proposed objective function. Figure 1a–f shows the original image, grey histogram, segmented image and the corresponding optimal grey threshold values obtained using the J_{max3}. The above said procedure is repeated for the image dataset shown in Table 1. It presents the objective function and optimal threshold values obtained with the proposed and existing J_{max} values. As one may observe, the proposed optimization function J_{max3} is generally better than the alternatives, including the traditional Otsu's between-class variance (J_{max1}) that presents the worse results.

[1] http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/

Table 1 Objective function values and the corresponding optimal thresholds

	m	Objective function			Optimal thresholds		
		J_{max1}	J_{max2}	J_{max3}	J_{max1}	J_{max2}	J_{max3}
Starfish	2	2864.4	2905.1	2965.2	82, 161	88, 153	76, 162
	3	2982.7	3083.7	3118.3	68, 120, 174	76, 133, 168	66, 136, 177
	4	3118.3	3165.1	3208.6	58, 106, 138, 186	72, 93, 127, 172	61, 127, 138, 179
	5	3515.9	3588.2	3632.5	53, 90, 116, 154, 189	61, 85, 121, 147, 180	56, 82, 135, 152, 183
Tiger	2	1594.1	1624.5	1693.2	51, 89	58, 92	48, 98
	3	1844.9	1904.6	1925.0	48, 76, 128	51, 72, 104	45, 77, 109
	4	2106.1	2197.5	2204.5	44, 72, 96, 133	46, 68, 101, 118	38, 74, 112, 120
	5	2185.5	2245.6	2284.1	35, 62, 89, 126, 147	35, 77, 84, 105, 134	34, 68, 81, 104, 130
Pheasant	2	605.88	695.14	717.40	74, 108	72, 112	68, 96
	3	823.73	893.55	846.37	52, 83, 113	48, 86, 119	53, 78, 104
	4	915.80	1085.1	1105.6	43, 65, 94, 122	38, 58, 88, 134	41, 62, 84, 122
	5	972.51	1142.5	1173.5	38, 72, 88, 106, 141	35, 78, 94, 112, 144	38, 72, 87, 106, 136
Flower	2	1282.4	1366.0	1357.3	66, 130	61, 127	62, 132
	3	1453.6	1492.4	1457.4	51, 83, 133	49, 77, 132	52, 78, 136
	4	1752.3	1824.2	1873.5	48, 66, 93, 146	46, 58, 87, 146	48, 52, 77, 145
	5	1993.6	2153.1	2177.1	41, 58, 92, 115, 153	41, 58, 92, 115, 153	40, 56, 88, 103, 154
Bison	2	2930.1	3085.2	3096.2	104, 172	104, 172	103, 178
	3	3027.3	3118.3	3166.4	74, 126, 178	69, 133, 185	62, 141, 189
	4	3317.2	3407.9	3411.5	61, 83, 105, 189	57, 80, 128, 188	52, 81, 136, 194
	5	3475.0	3533.4	3562.6	53, 64, 93, 143, 194	48, 75, 120, 129, 196	45, 78, 126, 172, 203

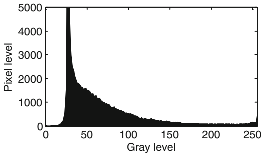
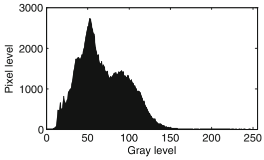
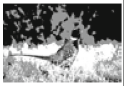
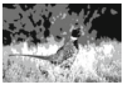
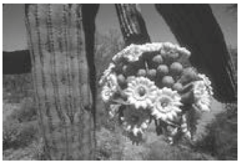
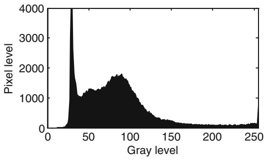
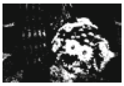
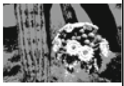
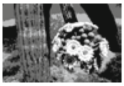
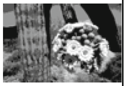
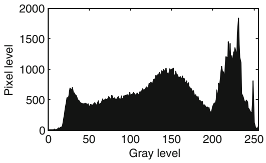
Table 2 depicts the performance measure values, such as, PSNR, SSIM, and the CPU time obtained with proposed and existing J_{max} values. As before, Table 2 depicts that despite small differences, the existing (J_{max1}) and proposed (J_{max2} and J_{max3}) OF-based search seem to reach the vicinities of the optimal solution (Table 3).

Despite the general superior performance depicted by the proposed method for all the tested images with various threshold levels (OF, PSNR, and SSIM values), the CPU time of J_{max1} is generally better than J_{max2} and J_{max3} for the considered trials. The proposed method offers better performance measure compared to the traditional objective function in the literature. From these results, it is noted that, the

Table 2 Performance measure values for the test images (mean value of 20 trials)

	m	PSNR (dB)			SSIM			CPU time (min)		
		J_{max1}	J_{max2}	J_{max3}	J_{max1}	J_{max2}	J_{max3}	J_{max1}	J_{max2}	J_{max3}
Starfish	2	14.051	16.063	16.267	0.6626	0.6707	0.6772	0.1861	0.2087	0.2146
	3	17.368	18.022	18.075	0.6852	0.7126	0.7169	0.2930	0.3102	0.3273
	4	19.252	19.722	19.817	0.7257	0.7297	0.7310	0.3201	0.3294	0.3611
	5	20.713	21.088	21.159	0.7602	0.7704	0.7802	0.4688	0.4438	0.5156
Tiger	2	15.974	16.732	16.781	0.7063	0.7158	0.7315	0.2063	0.2404	0.2481
	3	17.348	17.510	17.704	0.7326	0.7352	0.7368	0.2167	0.2517	0.2618
	4	19.005	19.138	19.211	0.7722	0.7804	0.7825	0.2318	0.2864	0.3066
	5	19.813	20.072	20.093	0.7839	0.7892	0.7875	0.3426	0.3573	0.3711
Pheasant	2	14.087	14.467	14.512	0.6428	0.6625	0.7063	0.2335	0.2555	0.3013
	3	15.257	15.963	15.377	0.6814	0.7042	0.7205	0.2494	0.2710	0.3262
	4	15.764	16.138	16.253	0.7063	0.7092	0.7315	0.3178	0.3472	0.3900
	5	16.085	16.833	17.192	0.7235	0.7422	0.7384	0.3295	0.4085	0.4316
Flower	2	17.061	17.477	18.245	0.7051	0.7175	0.7084	0.3185	0.3613	0.3604
	3	17.244	17.785	18.536	0.7146	0.7306	0.7249	0.3203	0.4084	0.4214
	4	17.530	18.033	19.147	0.7283	0.7514	0.7551	0.3522	0.4277	0.4336
	5	17.842	18.174	19.423	0.7300	0.7566	0.7604	0.3841	0.5123	0.5088
Bison	2	16.874	16.883	17.148	0.6752	0.6811	0.6901	0.2178	0.3665	0.4106
	3	17.178	17.568	17.730	0.6804	0.6905	0.6912	0.2540	0.3932	0.4332
	4	17.864	17.925	19.062	0.6916	0.7055	0.7216	0.3183	0.4087	0.4374
	5	18.299	18.315	19.136	0.7036	0.7117	0.7315	0.3511	0.4218	0.4500

Table 3 Test images, histogram, and segmented images with J_{max3}

	Image	Histogram	m = 2 m = 4	m = 3 m = 5
Tiger				
				
Pheasant				
				
Flower				
				
Bison				
				

proposed multiple objective function based procedure offers better performance measure values for the image segmentation problems.

5 Conclusions

In this paper, weighted sum of multiple Objective Functions (OF) are proposed to solve the Otsu based image thresholding problem. Bat Algorithm (BA) based optimization search is considered to obtain the bi-level and multi-level threshold values. The segmentation procedure is validated using both qualitative and quantitative analysis, including traditional measures, such as objective function, PSNR, SSIM, and CPU time. Results demonstrate that existing OF show a better CPU time when compared to the proposed OF. Nevertheless, the proposed OF, namely J_{max3}, is able to achieve a superior segmented image quality when compared to the alternatives.

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