ISSN: 2472-3703 DOI: 10.6911/WSRJ.202011_6(11).0003

Bat Algorithm Used for Multilevel Image Thresholding Segmentation

Suping Liu

College of Software Engineering, Guangdong university of science and technology, Dongguan, Guangdong 532000, China.

Abstract

In this paper, optimal thresholds for multi-level thresholding in image segmentation are gained by maximizing Otsu's between-class variance using bat algorithm (BA). The performances of the proposed algorithm are demonstrated by considering four benchmark images. The performance assessment is carried using peak-to-signal ratio (PSNR) and root mean square error (RMSE). The experiment results show that the more threshold, the better the segmentation effect.

Keywords

Bat algorithm; multilevel thresholding; image segmentation; Otsu.

1. INTRODUCTION

Image segmentation plays a important role in image preprocessing, it is wildly used in computer vision, pattern recognition and damage detection [1-2]. Over the years, several techniques for segmentation have been proposed and implemented in the literature [3], but, Thresholding is considered the most desired procedure out of all the existing procedures used for image segmentation, because of its simplicity, robustness, accuracy, and competence [4-5]. If the image can be divided into two classes, such as the background and the object of interest, it is called bi-level thresholding. Further more bi-level thresholding also can be extended to multilevel thresholding to obtain more than two classes [6]. In the non-parametric approaches, the thresholds are determined by maximize some criteria, such as between-class variance or entropy measures [7].

Traditional methods work well for a bi-level thresholding problem, when the number of threshold value increases, computing complexity of the thresholding problem also will increase. Therefore, the traditional method is different to get the desirable result. Hence, in recent years, kinds of heuristic search algorithms are applied to solve for the multilevel threshold such as BFO ABC CS and so on. In this work, the BA is adopted for solving multilevel thresholding image segmentation problem using Otsu's between-class variance method [8].

2. METHODOLOGY

Multilevel Thresholding image segmentation method are employed to find the best possible threshold in the segmented histogram by satisfying some guiding parameters. Otsu based image thresholding is initially proposed in 1979[15]. A detailed description of the between-class variance method could be found in bi-level thresholding (for m=2), input image is divided into two classes such as A0 and A1 (background and objects) by a threshold at a level “t.”The class A0 encloses the gray levels in the range 0 to t-1 and class A1 encloses the gray levels from t to L-1. The probability distributions for the gray levels A0 and A1 can be expressed as

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$$A_0 = \frac{p_0}{\omega_0(t)} \cdots \frac{p_{t-1}}{\omega_0(t)},\ A_1 = \frac{p_t}{\omega_1(t)} \cdots \frac{p_{L-1}}{\omega_1(t)} \tag{1}$$

Where, pi is the gray level probability, $\omega_0(t) = \sum_{i=0}^{t-1} p_i,\ \omega_1(t) = \sum_{i=t}^{L-1} p_i, and\ L = 256.$ And, the mean levels μ0 and μ1 for C0 and C1 can be measured by

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

The mean intensity(μT) of the entire image can be described as

$$u_T = \omega_0\mu_0 + \omega_1 u_1,\quad \omega_0 + \omega_1 = 1 \tag{3}$$

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

$$F_t^{opt} = \arg\max(\delta_0 + \delta_1) \tag{4}$$

Where, $\sigma_0 = \omega_0(u_0 - u_T)^2$ and $\sigma_1 = \omega_1(u_1 - u_T)^2$.

The bi-level thresholding can be extended to multilevel thresholding problem by increase the various “m” values as follows. Let us consider that there are “m” thresholds (t1, t2,...,tm), which divide the image into “m”classes: A0 with gray levels in the range 0 to t-1, A1 with enclosed gray levels in the range t1 to t2-1,..., and Am with gray levels from tm to L-1.The objective function for the multilevel thresholding problem can be expressed as

$$F_t^{opt} = \arg\max(\delta_0 + \delta_1 + \ldots + \sigma_m) \tag{5}$$

Where, $\sigma_0 = \omega_0(u_0 - u_T)^2, \sigma_1 = \omega_1(u_1 - u_T)^2, \ldots, \sigma_m = \omega_m(u_m - u_T)^2$.

3. BA ALGORITHM

The BA algorithm is new population based metaheuristic approach proposed by Xin-She Yang. In BA algorithm, initialization of the bat population is performed randomly. In our simulations, we use virtual bats naturally. Namely, generating new solutions is performed by moving virtual bats according to the following equations:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \tag{6}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x*)f_i \tag{7}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{8}$$

A random walk with direct exploitation is used for the local search that modifies the current best solution according the equation:

$$x_{new} = x_{old} + \partial A^t \tag{9}$$

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Where $\partial \in$ [-1,1] is a random number, while At is the average loudness of all the best at this time step. The local search is launched with the proximity depending on the rate ri of pulse emission. As the loudness usually decreases once a bat has found its pray, while the rate of pulse emission increases, the loudness can be chosen as any value of convenience. Hence, both characteristics imitate the natural bats. Mathematically, these characteristics are captured with the following equations:

$$A_i^{t+1} = \alpha A_i^t, r_i^t = r_i^0\left[1 - \exp(-\gamma t)\right] \tag{10}$$

Where α and γ are constants. Actually, α parameter plays a similar role as the cooling factor of a cooling schedule in the simulated annealing.

4. EXPERIMENTS RESULTS AND ANALYSIS

The popular performance indicator, peak signal to noise ratio (PSNR) is used to compare the segmentation results by using the multilevel image threshold method. The PSNR is measured in decibel (dB) as

$$PNSR = 20\log_{10}\left(\frac{255}{RMSE}\right), (dB) \tag{11}$$

where RMSE is the root mean-squared error, defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I(i,j) - \hat{I}(i,j)\right)^2}{M * N}} \tag{12}$$

Here I and $\hat{I}$ are original and segmented images of size $M * N$, respectively.

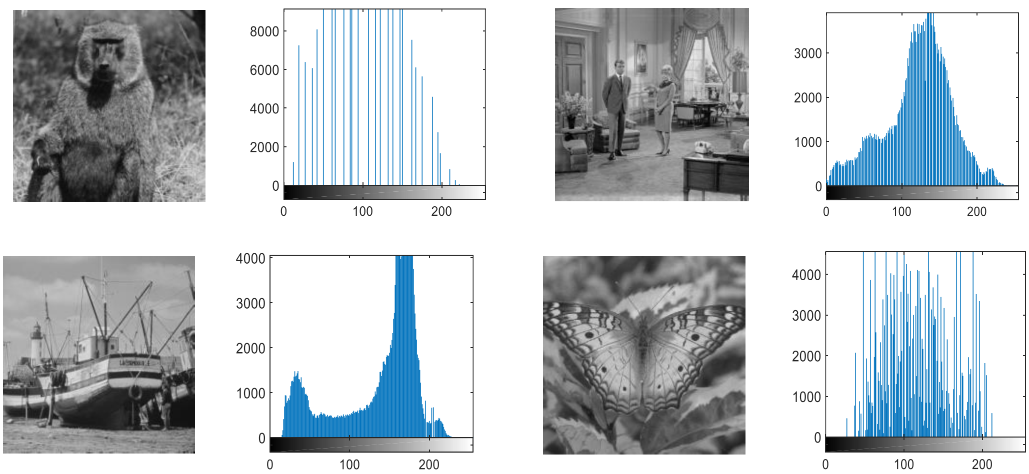

Fig 1. The test images and their histograms

In order to verify the performance of the method, Four test images are used to implement this experiment. The performance metrics for checking the effectiveness of the method are chosen as the PSNR and RMSE. At first, we focus on the image segmentation quality sensitivity to the number of thresholds k. Table 1 shows the selected thresholds, RMSE value and PSNR

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value with different thresholds. The RMSE is decrease and the PSNR is enlarge, and the threshold is evenly distributed.

Table 1. Experiment results based on Otsu

Images	k	Thresholds	RMSE	PSNR
Monkey	2	70 127	1.2060	19.3369
	3	67 121 175	0.7745	23.2412
	4	56 99 143 186	0.5744	25.8146
	5	50 86 124 155 186	0.5248	26.6019
Couple	2	87 145	1.1164	20.0113
	3	75 124 162	0.7942	22.9971
	4	59 102 137 171	0.6101	25.2291
	5	55 93 125 150 182	0.4944	27.0670
Boats	2	82 146	1.2463	19.1150
	3	67 123 164	1.0378	20.6803
	4	51 101 143 171	0.8680	22.1598
	5	44 84 125 155 177	0.6371	24.7347
Butterfly	2	97 149	1.0920	20.2549
	3	80 118 161	0.8567	22.3471
	4	71 97 126 161	0.7482	23.5061
	5	60 89 119 150 177	0.5749	25.7807

5. CONCLUSION

In this paper, optimal multilevel image thresholding problem is addressed using Otsu guided BA. The proposed histogram based bounded search technique helps in reducing the computation time. The PSNR and RMSE are adopted to evaluate the performance of the algorithm, the simulation results show that as the number of threshold increases, the segmentation effect is better. It is an effective method in image segmentation.

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