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Multilevel Image Thresholding based on Kapur's Entropy Using Cuckoo Search Algorithm

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Abstract

In this paper, optimal thresholds for multi-level thresholding in image segmentation are gained by maximizing Kapur's entropy using cuckoo search algorithm (CS). and the between-class variance is taken as the object function to compared with Kapur's entropy. The performance assessment is carried using peak-to-signal ratio (PSNR). The experiment results show that the more threshold, the better the segmentation effect and the Kapur's entropy in image segmentation is better than the between-class variance.

Keywords

cuckoo search algorithm; multilevel thresholding; image segmentation; Kapur's entropy.

1. Introduction

Image segmentation plays an important role in image preprocessing, it is wildly used in computer vision, pattern recognition and automatic drive Over the years, several methods for segmentation have been proposed by researchers in the literature [1-3]. However, image thresholds segmentation 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]. Assume an image can be divided into two classes, such as the background and the object of interest, it is called bi-level thresholding. Furthermore, 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].

Bi-level thresholding problem relatively easy to solve. But, when the number of threshold value increases, computing complexity of the thresholding problem also will increase. Multilevel threshold problem is a NP-hard problem [8]. Therefore, the traditional method is different to get the desirable results. In recent years, heuristic search algorithms are proposed. Hence, kinds of heuristic search algorithms are applied to solve for the multilevel threshold such as ABC, FA , BA and so on.

In this work, the CS is adopted for solving multilevel thresholding image segmentation problem using Kapur's entropy.

The paper is organized as follows. Section 2 presents the multilevel thresholding based Kapur's entropy. Section 3 presents the overview of the CS. Experimental results are evaluated and discussed in Section 4. Conclusion of the present research work is given in Section 5.

2. Kapur's Entropy in Multilevel Image Thresholding

For an image with L gray levels, let $P_i=P_0$, $P_1, ..., P_{L-1}$ be the probability distribution of the gray levels, P_i can be calculated by

$$N = \sum_{i=0}^{L-1} h(i),\ P_i = h(i)/N \tag{1}$$

In particular, h(i) denotes the number of occurrences of gray-level i. N denotes total number of pixels in the image.

Entropy is basically a thermodynamic concept associated with the order of irreversible processes from a traditional point of opinion. Kapurs entropy defined as follow [8]

$$K(A) = -\sum_{i=1}^{n} p_i \ln p_i \tag{2}$$

Assume that a gray image can be divided into two classes, one for the object (class A_1), and the other for the background (class A_2). Accordingly, for each class, Kapur's entropy can be expressed as:

$$K^{A_1}(t) = -\sum_{i=0}^{t} \left(P_i / P^{A_1}\right)\ln\left(P_i / P^{A_1}\right) \tag{3}$$

$$K^{A_2}(t) = -\sum_{i=t+1}^{L-1} \left(P_i / P^{A_2}\right)\ln\left(P_i / P^{A_2}\right) \tag{4}$$

Where,

$$P^{A_1} = \sum\nolimits_{i=0}^{t} P_i,\ P^{A_2} = \sum\nolimits_{i=t+1}^{L-1} P_i \\ \text{and } P^{A_1} + P^{A_2} = 1. \tag{5}$$

Kapur's entropy satisfies additive property

$$K(A_1 + A_2) = K(A_1) + K(A_2) \tag{6}$$

Moreover, suppose that an image can be divided into m+1 parts, m stands for the number of the threshold values. Hence, satisfying the following equation.

$$P^{A_1} = \sum_{i=0}^{t_1} P_i,\ \ P^{A_2} = \sum_{i=t_1+1}^{t_2} P_i, \cdots, P^{A_{m+1}} = \sum_{i=t_m+1}^{L\text{-}1} P_i\ . \tag{7}$$

$$P^{A_1} + P^{A_2} + \cdots + P^{A_{m+1}} = 1 \tag{8}$$

The multilevel image thresholding based on Kapur's entropy can be express as following

$$K^{A_1}(t) = -\sum_{i=0}^{t_1} \left(P_i / P^{A_1}\right)\ln\left(P_i / P^{A_1}\right), \\ K^{A_2}(t) = -\sum_{i=t+1}^{t_2} \left(P_i / P^{A_2}\right)\ln\left(P_i / P^{A_2}\right) \\ \ldots,\ K^{A_{m+1}}(t) = -\sum_{i=t_m+1}^{L\text{-}1} \left(P_i / P^{A_{m+1}}\right)\ln\left(P_i / P^{A_{m+1}}\right) \tag{9}$$

The total Kapur's entropy of the image is measured by

$$K(A_1 + A_2 + \ldots + A_{m+1}) = \sum_{i=1}^{m+1} K(A_i) \tag{10}$$

The optimal multilevel thresholding is configured by maximizing the objective function

$$K^{opt} = \operatorname{argmax}\left[K(A_1 + A_2 + \ldots + A_{m+1})\right] \tag{11}$$

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3. Cuckoo Search Algorithm

Recently, the Cuckoo Search (CS) algorithm is proposed by Yang and Deb [12]. CS is also a heuristic global search algorithm which is wildly used to solve different optimization problems. The following principles of CS algorithm are:

1. Interestingly, each cuckoo bird lays one egg at a time, and dumps its egg in a randomly chosen nest of another bird from other species.

2. Usually the best nests containing high quality eggs are carried over to the next generations.

3. The number of available host nests is fixed. And the egg laid by a cuckoo bird is discovered by the host bird with a probability $p_\alpha \in [0,1]$. Note that the worst nests are discovered and dropped from further calculations.

The choice of control parameters in CS algorithm is simple and required for implementing the algorithm. Note that the control parameters of the CS algorithm are the scale factor (β) and the mutation probability value (p_α). While generating new solution $x^{(t+1)}$, for a cuckoo *i*, a Levy flight is performed:

$$x_i^{t+1} = x_i^t + \alpha \oplus Levy(\lambda) \tag{12}$$

where $\alpha > 0$, is the step size. Here we choose $\alpha = 1$. Levy flights provide a random walk while their random steps are drawn from a Levy distribution for large steps defined by:

$$\text{Levy} \sim u = t^{-\lambda}, \ (1 < \lambda \leq 3) \tag{13}$$

which has an infinite variance and infinite mean.

4. Experiments Results and Analysis

4.1. Parameters Setting

The proposed method has been tested under a set of benchmark images. Some of these images are widely used in the multilevel image segmentation literature to test different methods (Hunter, House, Owl and Butterfly), as shown in Figure 1. The parameters of the CS are population size is 20, number of iterations is 200, threshold value range from 2 to 5. 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 [13]

$$PNSR = 20\log_{10}\left(\frac{255}{RMSE}\right), (dB) \tag{14}$$

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

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I(i,j) - \hat{I}(i,j)\right)^2}{M * N}} \tag{15}$$

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

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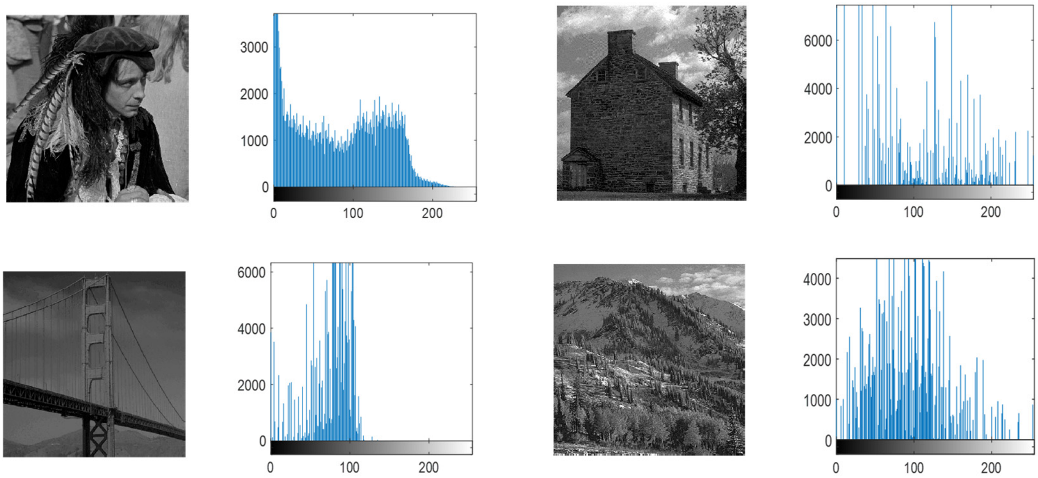

Figure 1. The test images and their histograms

4.2. Results based on Kapur's Entropy

Table 1. Results based on Kapur's entropy

Images	*k*	Kapur's entropy	
		Thresholds	PSNR
Hunter	2	91 178	19.2719
	3	58 116 178	22.7269
	4	45 89 132 178	25.2066
	5	45 89 132 177 221	25.4841
House	2	84 161	20.8879
	3	84 112 178	21.6735
	4	12 83 112 177	23.5900
	5	70 95 112 149 188	23.7275
Bridge	2	50 77	12.5883
	3	50 77 167	20.5692
	4	44 74 93 159	25.2106
	5	44 62 77 91 107	25.0721
Mountain	2	71 138	21.2025
	3	50 94 139	23.4039
	4	48 82 113 146	25.5198
	5	41 67 96 121 161	26.6442

5. Conclusion

In this paper, optimal multilevel image thresholding problem is addressed using Kapur's entropy guided CS The proposed histogram based bounded search technique helps in reducing the computation time. The PSNR is adopted to evaluate the performance of the algorithm, the simulation results show that as the number of thresholds increases, the segmentation effect is better. And, in comparison with Otsu, the method of Kapur's entropy in multilevel image segmentation is much better than the Otsu. It is an effective method in image segmentation.

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