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Image segmentation with a multilevel threshold using backtracking search optimization algorithm

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ABSTRACT

Image segmentation is an important process in image processing. Though, there are many applications are affected by the segmentation methods and algorithms, unfortunately, not one technique, but the threshold is the popular one. Threshold technique can be categorized into two ways either simple threshold which has one threshold or multi-thresholds separated which has more than two thresholds. In this paper, image segmentation is used simple threshold method which is a simple and effective technique. Therefore, to calculate the value of threshold solution which is led to increase exponentially threshold that gives multi-thresholds image segmentation present a huge challenge. This paper is considered the multi-thresholds segmentation model for the optimization problem in order to overcome the problem of excessive calculation. The objective of this paper proposed an algorithm to solve the optimization problem and realize multi-thresholds image segmentation. The proposed multi-thresholds segmentation algorithm should be segmented the raw image into pieces, and compared with other algorithms results. The experimental results that show multi-thresholds image segmentation based on backtracking search optimization algorithm are feasible and have a good segmentation.

1. Introduction

Image segmentation based on dividing an image into regions with different characteristics and extracting the interesting target. It is the basic step in image processing to produce the image analysis [1], and it is also a basic problem of computer vision [2]. Image segmentation has highly valued for many years. It has also various algorithms proposed so far, such as threshold-based segmentation methods[3], edge detection-based segmentation methods[4], and region-based segmentation methods, however, all of these methods didn't give a good result. Moreover, there are many methods are interested with image segmentation such as the graph theory-based segmentation[5]. The energy-based functional segmentation, and the machine learning-based image segmentation [6]. For example, threshold method is widely used in different image segmentation algorithms, the basic idea of this method is divided the gray level image into multiple parts, each part can be processed with one or more thresholds, and the gray values are stayed in the same class of the pixels belong to the same target [7]. Therefore, the

selection of the threshold is critical and determines the outcome of the segmentation. though, the common methods for calculating thresholds can be included the largest inter-class variance method (Otsu algorithm)[7], the maximum entropy method [8], and the minimum error method [9]. However, the previous methods for calculating threshold are basically obtained by analytical expression when a certain satisfied criterion. For example, selects the threshold by using the maximum variance between the target and the background or the minimum variance within the class. The amount of computational complexity is increased exponentially as the threshold increases. Therefore, some researchers regard the threshold solution problem based on the criterion function as the optimization problem of the objective function. Some multi-threshold methods based on genetic algorithm [10], particle swarm optimization algorithm and differential algorithm[11]. To solve multi-threshold problems there are some novel bionic algorithms used for such kinds of problems, and presented a better segmentation effects [12]. In this

paper is used BSA which is as emerging bionic algorithm with Simple structure, and can effectively and quickly solve various function optimization problems[13]. Therefore, to solve the validity of multi-threshold problems of image segmentation which is proposed BSA algorithm for multi-threshold image segmentation. The proposed method exploited the Otsu algorithm and the criterion function of the maximum entropy method as target function, and use BSA algorithm to obtain multiple thresholds respectively like splitting. The experiment shows that the proposed method has a better performance than the others. The reset of paper organized as follows, section 2 explain the threshold method, section 3 is the algorithm that used in algorithm BSA, section 4 explain the utilizing algorithm for image segmentation, section 5 is experiment result finally section 6 explain the conclusion.

2. Threshold Method

2.1 Maximum inter-class variance method (Otsu method): The maximum inter-class variance method gives the principle of discriminant analysis least squares. It divides the images into different categories according to the gray-scale characteristics of the image and the largest variance between the types. Suppose there is an image P of m-level gradation, the threshold q divides the gray value range [0, 1, ..., m-1] of the image into the background and the target with two parts. Let p_i also indicate the probability of the gray value i, and the probability of the target and the background can be expressed as [14]:

$$w_1 = \sum_{i=0}^q p_i \dots \dots \dots (1)$$

$$w_2 = \sum_{i=q+1}^{m-1} p_i \dots \dots \dots (2)$$

Let λ , λ_1 , and λ_2 represent the gray values of the image, target, and background, respectively, and it can be expressed as [15]:

$$\lambda_1 = \sum_{i=0}^q i p_i / w_1 \dots \dots \dots (3)$$

$$\lambda_2 = \sum_{i=q+1}^{m-1} i p_i / w_2 \dots \dots \dots (4)$$

$$\lambda = w_1 \lambda_1 + w_2 \lambda_2 \dots \dots (5), \text{ with } w_1 + w_2 = 1$$

The variance between classes can be expressed as [16]:

$$d(q) = w_1 (\lambda_1 - \lambda)^2 + w_2 (\lambda_2 - \lambda)^2 \dots \dots \dots (6)$$

According to the criterion of maximization between classes when the variance reaches to the maximum value, it can be obtained the optimal threshold q. Suppose image P has a threshold ($q_1, q_2, \dots, q_a$), in equation (5) It is easy to extend the multi-threshold class variance, which can be expressed as [17]:

$$d(q_1, q_2 \dots q_a) = w_1 (\lambda_1 - \lambda)^2 + \dots \dots + w_a (\lambda_a - \lambda)^2 \dots \dots (7)$$

According to the criterion for maximizing between classes, it can be obtained by calculating formula (8) optimal threshold [18]:

$$(q_1, q_2 \dots q_a) = \argmax(d(q_1, q_2 \dots q_a) \dots \dots \dots (8)$$

2.2. Maximum Entropy Method (Kapur Method): The idea of apply threshold for image segmentation is to use the gray scale distribution density function of the image to define the information entropy of the image

and to determine the threshold according to the optimization criteria. Some methods are determined threshold by maximizing the upper limit of the posterior [4], while others assume that the target and the background conform two different probability distributions therefore the information entropy is maximized to find the optimal threshold [5], Suppose there is an image P of m-level gradation, and the threshold q will be to the P image. The gray value range [0, 1, ..., m-1] is divided into the background and the target with two parts. Let p_i also indicates to the probability of the gray value i, then the target and background can be expressed in equation (1) and (2), and their information of entropy can be expressed as [19]:

$$H_1 = - \sum_{i=1}^q \frac{p_i}{w_1} \ln(\frac{p_i}{w_1}) \dots \dots \dots (9)$$

$$H_2 = - \sum_{i=q+1}^{m-1} \frac{p_i}{w_2} \ln(\frac{p_i}{w_2}) \dots \dots \dots (10)$$

The Kapur method [5] is to obtain the optimal threshold when the total information entropy of the image P is maximum, ie [20]:

$$q = \argmax(H_1 + H_2) \dots \dots \dots (11)$$

Similarly, equation (11) can easily be extended to multi-threshold maximum entropy, which can be expressed as [21]:

$$(q_1, q_2 \dots q_a) = \argmax(H_1 + H_2 + \dots + H_a) \dots \dots (12)$$

Where: α represents the number of thresholds.

3. Backtracking search optimization algorithm(BSA):

The BSA algorithm is an emerging stochastic optimization search technology, which has a simple structure and can effectively solve various optimization problems. In addition, the BSA algorithm is also a population-based search technique and uses an external document to maintain its historical population information to guide population evolution. When the BSA algorithm is used to solve optimization problems multi-threshold image segmentations are assisted by backtracking search optimization algorithm[7,5]. Suppose sample initialization candidate X and historical population X_{old} [22]:

$$x_{i,j,0} = x_{i,j,min} + r(x_{i,j,max} - x_{i,j,min}) \quad i = 1, 2, \dots NP \quad (13)$$

Where: $r \in [0,1]$ is a random number and NP is the population size. Similar to other evolutionary algorithms, the BSA algorithm uses three basic genetic operations: mutation, crossover, and selection. The BSA algorithm uses a random mutation strategy to generate an intermediate candidate V_m for each individual. This strategy can effectively use the information-guided algorithm evolution of historical populations. The specific formula is [23]:

$$V_m = X + F(V_{old} - X) \dots (14)$$

Where: F scaling factor is used to control the search direction matrix. Second, the BSA algorithm is in the variant individual V_m and the current population X based on non-uniform and complex cross-strategy to generate candidate solutions T. This strategy

generates a mapping matrix map in a random manner. (NP × D), and map the information in V_m and X

according to the matrix T. The crossover strategy can be summarized as shown below.

Algorithm 1: cross strategy [24]

```

Input variant individual  $V_m$ , population X, population size NP, sk
The dimension D, and the mixing rate mix_rate.
Output candidate solution T
1) Initialization matrix map(1:NP, 1:D) = 1;
2) uniformly generating random numbers a and b between 2 [0, 1];
3) if a>b, transfer to 4), otherwise transfer to 5);
4) Proceed to the following steps and proceed to step 6:
   For i =1 to NP
     Randomly generated series u = permuting(1:D);
     Uniformly generate a random number c between [0, 1];
     Process map( i ,1:u ( 1:mixrate× c × D )) = 0;
   End for
5) Do the following:
   For i =1 to NP
     Uniformly generate a random integer d between [0, D];
     Process map( i ,d ) = 0;
   End for
6) T =  $V_m$ ;
7) Do the following:
   For i =1 to NP
     For j =1 to D
       If map( i ,j ) = 1 then T( i ,j ) = P( i ,j );
     End for
   End for

```

In addition, the BSA algorithm uses two selection operations. First choice Select the operation to update the information of the historical population, which is completely random Receiving current population information, which can be summarized as [25]
: if $a > bX_{old} = X | a, b \sim U(0, 1) \dots \dots (15)$

4. Apply BSA to solve multiple

thresholds: The BSA algorithm is applied to solve the multi-threshold problem. The significance of use the multi-threshold criterion as the objective function and the BSA algorithm to search for the optimal threshold value and the specific steps which are shown below:

Algorithm 2 :Multi-threshold image segmentation based on BSA algorithm [26]

```

Enter the population size NP, dimension D (the number of thresholds), mix_rate,
maximum iteration number Max Iteration.
Output optimal threshold q
1) Initialize population X and historical population  $X_{old}$  using equation (12);
2) Initialize the iteration counter iter=1;
3) if iter>MaxIteration, transfer to 11);
4) Execute the first selection operation, that is, execute the (14) update calendar
   Historical population
5) Perform the mutation operation, that is, execute the equation (13);
6) Perform a crossover operation to obtain T, that is, execute algorithm 1;
7) evaluating T by using formula (7) or formula (11);
8) According to the adaptation values of X and T, the second selection operation is
   adopted.
   Get the next generation of population X.
9) obtaining the current optimal threshold q;
10) iter = iter+1, transfer to 3);
11) Output an optimal threshold q.

```

5. Experiments and results: In order to analyze the multi-threshold image segmentation performance of the BSA algorithm, in this paper can be used ball (one object), Lena (one object),

Peppe r (multi-object), and Baboon (one object) which are shown in figure (1) with the size of each jbg image is 256 x 256[27] .



Fig. 1: image testing

When executed by matlab 2015 the segmentation threshold for BSA algorithm the result for threshold

equal=5 the images shown in figure(2):

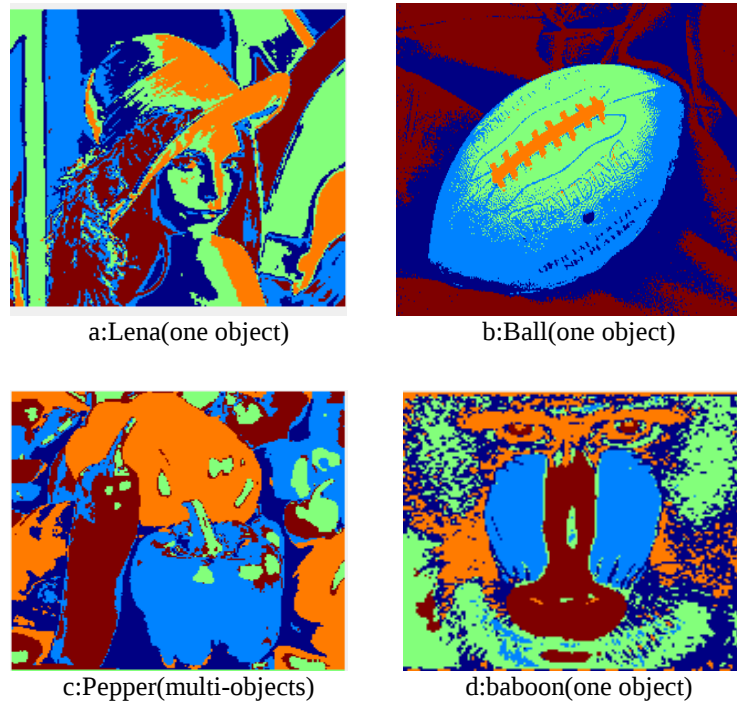


Fig. 2: the results of BSA algorithn(threshold=5)

In addition, the peak signal to noise ratio- (PSNR) is used as a performance indicator, and the PSNR formula is as follows [28,29]:

$$PSNR = 20 \log_{10} \left(\frac{255}{RMSE} \right) \dots \dots (15)$$

While

$$RMSE = \sqrt{\frac{1}{M \cdot N} \sum_{i=1}^M \sum_{j=1}^N (I(i,j) - J(i,j))^2} \dots \dots (16)$$

Where: the image I size is M×N, and J is the threshold image. In the experiment, each algorithm

runs independently 30 times for each image. In each independent run, the maximum number of iterations, Max Iteration, is 160, the population size NP is 20.

5.1. Experimental results of the Otsu method:

Table 1 gives the experimental results compared with

the multi-threshold Otsu (MOT) [28] based on the traditional optimization algorithm. The fitness value in the MOT is obtained by taking the threshold in the MOT into equation (8).

Table 1: experimental results compared with the multi-threshold Otsu (MOT)

Testing image	Threshold number	multi-threshold Otsu		Backtracking search optimization	
		Adaptation value	PSNR	Adaptation value	PSNR
Lena	2	2895.36	12.67	2923.59	13.65
	3	3136.52	15.83	3174.38	17.16
	4	3238.31	18.01	3271.09	19.38
	5	3276.55	18.93	3309.5	20.94
Ball	2	3927.9	11.14	3929.46	11.12
	3	4010.71	12.72	4012.3	12.85
	4	4053.73	16.13	4069.13	16.38
	5	4092.03	19.87	4103.01	19.17
Pepper	2	3142.25	12.5053	3180.47	12.87
	3	3364.89	15.16	3396.53	16.57
	4	3445.22	16.28	3476.78	17.69
	5	3489.22	17.04	3533.00	19.47
Baboon	2	1566.1	12.49	1742.75	15.85
	3	1722.19	13.93	1865.12	18.22
	4	1782.34	14.64	1934.25	19.69
	5	1821.35	15.22	1967.98	21.53

It can be seen in table 1 that the threshold value that is solved by the BSA algorithm makes the adaptation value better than the value that is obtained from MOT and PSNR. However, the results that appear in table 2 are shown that the BSA algorithm which is solved by the multi-threshold with the maximum inter-class criterion of Otsu as the objective function and Feasible which get better performance. Therefore, It can be seen from Table 2 that compared with the BFA algorithm, the multi-threshold value solved by the BSA algorithm is obviously superior in the objective function adaptation value and PSNR. In addition, with comparison with the PSO algorithm,

the multi-thresholds solved by the BSA algorithm are the same as the multi-thresholds solved by the PSO algorithm at the 2 and 3 thresholds of each test image. However, at 4 and 5 thresholds, the PSO algorithm is slightly better and a good objective function adapts to the value, but the BSA algorithm gets a better PSNR. In general, the multi-threshold performance of the BSA algorithm is the same as the multi-threshold performance of the inertia weighted PSO algorithm. Therefore table 2 shows the PSNR trends to solve by the BSA algorithm which is generally the best number of thresholds increases.

Table 2: Otsu function, PSNR, BFA algorithm, PSO algorithm and BSA algorithm

Testing image	Threshold number	BFA		PSO		BSA	
		Adaptation value	PSNR	Adaptation value	PSNR	Adaptation value	PSNR
Lena	2	2923.5875	14.75	2923.59	13.65	17.72	14.62
	3	3165.8755	17.21	3174.28	17.16	21.98	17.10
	4	3243.8855	18.55	3271.09	19.27	25.84	18.96
	5	328119.83	19.83	3309.5	20.81	29.52	20.71
Ball	2	17.55	11.66	3929.46	11.12	3929.46	11.12
	3	21.95	15.50	4012.3	12.85	4012.3	12.85
	4	26.29	19.13	4069.16	18.94	4069.13	16.38
	5	30.23	20.91	4103.2	17.86	4303.01	19.17
Pepper	2	3180.16	12.79	3180.47	12.87	3180.47	12.87
	3	3394.44	15.25	3396.53	16.57	3396.53	16.57
	4	3454.18	16.55	3476.79	17.68	3476.78	17.69
	5	3606.14	17.78	3533.05	19.20	3533.00	19.47
Baboon	2	1742.52	15.10	1742.75	15.85	1742.75	15.85
	3	1856.36	16.97	1865.12	18.22	1865.12	18.22
	4	1905.70	19.59	1934.27	19.69	1934.25	19.69
	5	1961.01	21.20	1968.39	21.25	1967.98	21.53

Table 3: Apur function, PSNR ,BFA algorithm, PSO algorithm,BSA algorithm

Testing image	Threshold number	BFA		PSO		BSA	
		Adaptation value	PSNR	Adaptation value	PSNR	Adaptation value	PSNR
Lena	2	2923.58	14.75	17.72	14.62	17.72	14.62
	3	3165.87	17.21	21.98	17.03	21.98	17.1
	4	3243.88	18.55	25.84	19.19	28.96	18.96
	5	3281.39	19.83	29.52	20.64	29.52	20.71
Ball	2	3929.46	11.12	17.56	12.08	17.56	12.08
	3	4010.73	12.6	21.97	18.69	21.97	15.69
	4	4056.59	14.33	26.54	18.99	26.54	19.01
	5	4090.59	16.16	30.59	20.23	30.50	20.05
Pepper	2	3180.16	13.22	18.14	13.22	18.19	13.45
	3	3394.44	16.64	22.53	16.34	22.53	16.49
	4	3454.18	18.64	26.66	18.79	26.98	18.89
	5	3506.14	19.55	30.59	20.02	31.06	20.22
Baboon	2	1742.52	14.81	17.22	14.81	17.56	15.04
	3	1856.36	15.59	21.48	16.75	21.67	16.95
	4	1905.70	17.71	28.44	17.78	29.02	18.17
	5	1961.01	18.62	29.13	20.16	29.13	21.34

5.2. Experimental results: Table 3 shows the comparison results of different bionic algorithms for solving the Kapur multi-threshold, where the parameters are the same as in Section 4.1. It can be seen from Table 3 that the BSA algorithm solves the objective function adaptability value completely better than the BFA algorithm's objective function adaptation value, and with the PSNR performance, the BSA algorithm is also superior to the BFA algorithm. In addition, compared with the PSO algorithm, the objective function solved by the BSA algorithm is suitable. The values should be basically similar, but with the help of PSNR, the multi-threshold of the BSA algorithm. The value method is generally superior to the multi-threshold method of the PSO algorithm. Figure 3 shows the trend of the PSNR of each bionic algorithm as a function of the Kapur threshold. It can be seen from Figure 3 that on

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- most images, the PSNR of the BSA solution is better than the other two algorithms with the Kapur threshold.

Conclusion

In conclude , the BSA algorithm is applied for image segmentation and multi - threshold image segmentation. The proposed method is used the multi-threshold criterion function of Otsu method and Kapur method as the objective function. Therefore, the BSA algorithm is used to solve and realize image segmentation. The simulation results show that the multi-threshold image segmentation which is solved by BSA algorithm is possible. In comparative with the multi-threshold segmentation method which is solved by BFA algorithm and PSO algorithm, the proposed method has better performance than the others.

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تجزئة الصورة بعتبة متعددة المستويات باستخدام خوارزمية التحسين الراجع

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الملخص

تجزئة الصورة هي عملية مهمة في معالجة الصور الرقمية .وعلى الرغم من ذلك،هنالك العديد من التطبيقات التي تتأثر بطرق وخوارزميات التجزئة،ولسوء الحظ ،لا توجد تقنية واحدة،ولكن استخدام تقنية العتبة هي الأكثر شعبية.حيث يمكن تصنيف تقنية العتبة الى طريقتين هما عتبة بسيطة أي لها عتبة واحدة او عتبات متعددة مفصولة تضم اكثر من عتبة.ففي هذه الورقة يتم تجزئة الصورة الخام باستخدام طريقة العتبة البسيطة وهي تقنية بسيطة وفعالة ،ولحساب قيمة العتبة التي أدت الى زيادة قيمتها أسيا والذي يؤدي الى تجزئة الصور الى عتبات متعددة يعتبر تحديا كبيرا.تعتبر هذه الورقة انموذج للتجزئة المتعددة الحدود لمشكلة التحسين وهي للتغلب على مشكلة الحساب الزائد.ان الهدف من الخوارزمية المقترحة هو حل مشكلة التحسين وتحقيق تجزئة متعددة الحدود للصور الرقمية.وحسب النتائج التي تظهر للتجزئة متعددة الحدود استنادا الى خوارزمية تحسين البحث تراجعا (الطريقة المقترحة)اثبتت انها طريقة ملائمة ولها تجزئة جيدة.