Applications of dynamic adaptive bee colony algorithm in multi-threshold image segmentation

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Abstract

Artificial bee colony (ABC) is an evolutionary computation method, which is inspired from the specific collaborative social group behaviour among the individual bees in the colony and which is a heuristic optimization algorithm based on population search strategy. This paper has proposed a quick dynamic adaptive bee colony algorithm, which analyses the performances of the artificial bee colony algorithm and it designs a multi-threshold image segmentation method realizing a dynamic adaptive artificial bee colony (DAABC) with multi-threshold OTSU as the fitness function. The main characteristics of this method include: reducing the noise interferences in the multi-threshold image segmentation; effectively narrowing down the search range of the threshold; guaranteeing the quickness of the segmentation speed; determining the search range of the reconnaissance ants with adaptive dynamic control and accelerating the convergence speed of bee colony algorithm. The experimental results demonstrate that the method in this paper is better than the image segmentation method based on particle swarm optimization (PSO) and artificial fish swarm algorithm (AFSA).

Keywords: Artificial Bee Colony Algorithm, Multi-Threshold, Image Segmentation, OTSU

1 Introduction

ABC is a newly-emerging intelligent heuristic algorithm, which was proposed by Professor Karaboga in Erciyes University in 2005 and it comes from the research and simulation of honey-collecting behaviour of the bees. Compared with PSO, ant colony optimization (ACO) and differential evolution (DE), this method has simple operations, fewer parameters and strong robustness; therefore, it has attracted extensive attention of domestic and international scholars and it has successfully settled numerous practical problems. However, since ABC hasn't appeared until the recent years, it still has a short development history and there are still many problems to be solved, including the weak theoretical support, the critical times setting of the appearance of reconnaissance bee and the search behaviour of the honey-collecting bees.

The improvements of ABC mainly include the following three aspects: (1) the improvements of the search behaviour of the honey-collecting bees, including the suppression of bad food sources from becoming the neighbourhood bees and the accelerated movements the honey-collecting bees make on the excellent food sources; (2) the replacements of bad food sources. In the population evolution, replace the bad food sources in a narrow space in every circle to improve the quality; (3) the improvements of the appearance of the reconnaissance bees. In a new search, since the food sources which have been abandoned for too many retention times have been differentiated for the position in the population, adopt reverse learning strategy if it is global optimal; otherwise, cross them with better food sources[1].

In recent years, OTSU based on the maximum between-cluster variance has been successfully used in image dual threshold segmentation. This paper realizes multi-threshold image segmentation with OTSU. Additionally, it has used it in the artificial bee colony search algorithm and proposed a dynamic adaptive bee colony algorithm to analyse the value and status of bee colony algorithm in multi-threshold image segmentation.

2 The construction of the objective function in multi-threshold image segmentation

2.1 THE CONSTRUCTION OF OBJECTIVE FUNCTION

Firstly, assume that a grey-scale image can be shown with L grey scales ($L \in [1,256]$); the possibility for the pixel with i grey scales is $P_i(P_i = \frac{f_i}{N}, P_i > 0, \sum_{i=1}^{L} P_i = 1)$; f_i is the sum of the pixels with i grey scales and N is the total pixels of the image. If the threshold t segments the image l into the objective and the background, then the possibilities of the objective and the background are ω_0 and $\omega_1(t)$ separately and the mean value of the objective and the background are $\mu_0(t)$ and $\mu_1(t)$ and $\omega_0 + \omega_1 = 1$.

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In the above formula, $\omega_0 = \sum_{i=0}^{t} P_i$, $\omega_1(t) = \sum_{i=t+1}^{L-1} P_i$, $\mu_0(t) = \sum_{i=0}^{t} iP_i / \omega_0$ and $\mu_1(t) = \sum_{i=t+1}^{L-1} iP_i / \omega_1$, $\omega_0 = \sum_{i=0}^{t} P_i$, $\omega_1(t) = \sum_{i=t+1}^{L-1} P_i$, $\mu_0(t) = \sum_{i=0}^{t} iP_i / \omega_0$, $\mu_1(t) = \sum_{i=t+1}^{L-1} iP_i / \omega_1$. Then the difference between the objective and the target is: $D(t) = \omega_0(t)\omega_1(t)(\mu_0(t) - \mu_1(t))^2$. Therefore, t with the biggest difference is the optimal threshold.

As mentioned above, assuming that the thresholds of the image to be segmented are m, then its difference is:

$$\begin{aligned} D(t_1, t_2, \ldots, t_m) &= \omega_0\omega_1(\mu_0 - \mu_1)^2 + \omega_0\omega_2(\mu_0 - \mu_2)^2 \\ &+ \cdots + \omega_0\omega_m(\mu_0 - \mu_m)^2 + \omega_1\omega_2(\mu_1 - \mu_2)^2 \\ &+ \omega_1\omega_3(\mu_1 - \mu_3)^2 + \cdots + \omega_{m-1}\omega_m(\mu_{m-1} - \mu_m)^2 \end{aligned} . \quad (1)$$

In the formula, $\omega_{m-1} = \sum_{i=t_{m-1}+1}^{t_m} P_i$ and $\mu_{m-1} = \sum_{i=t_{m-1}+1}^{t_m} iP_i / \omega_{m-1}$. Assuming the segmentation threshold of the image is $(t_1^*, t_2^*, \ldots, t_m^*)$, then the optimal threshold of the image to be segmented is $(t_1^*, t_2^*, \ldots, t_m^*) = \underset{0 \le t_1 \le t_2 \ldots \le t_m}{Arg \max} D(t_1, t_2, \ldots, t_m)$ from the below formula according to DAABC [2, 3].

2.2 THE FEASIBILITY ANALYSIS OF THE OBJECTIVE FUNCTION

In the swarm intelligent optimization algorithm, the fitness function has a significant importance on the population optimization and it guides the population to forage or evolve towards a certain direction and finally reaches the optimal status.

This method sees the image threshold as the bee of the ABC and designs the fitness function of ABC through two-dimensional OTSU and it gets closer to the optimal threshold generation by generation through the collaboration and information share of the honey-collecting bees, the reconnaissance bees and the observing bees [4].

ABC searches the optimal nectar source through the collaboration and information share of the honey-collecting bees, the observing bees and the reconnaissance bees. The following analyses the working mechanism of the bee population by integrating the application environment of this paper. When ABC is used in the image segmentation, every nectar source position corresponds to a threshold and the honey volume of the nectar source corresponds to the fitness function value. The honey-collecting bee produces and compares a new position by searching the neighbourhood according to its memory. If the new position is superior to the optimal position in memory, replace it with the new position; otherwise, keep the original optimal position [5]. After all the honey-collecting bees finish searching, they share and nectar source information with the observing bees through “swing dance” and then the observing bees choose a nectar source position with the possibility related to the honey volume according to the information obtained and search and produce a new position by searching near the nectar source. After that, they compare with the previous position and always remember the optimal position. If a nectar source can’t be improved through limited circulations, then abandon it and use the new position randomly producing by the reconnaissance bees [6].

In the bee colony search algorithm, the number of nectar sources can be seen as the number of thresholds of the image to be segmented, namely the number of variables of OTSU function. Every nectar source is deemed as the possible threshold of the image, namely the parameter $(t_1, t_2, \ldots, t_m)$ of OTSU function and when segmented 256-greyscale image, $(t_1, t_2, \ldots, t_m)$. Therefore, the objective function of the multi-threshold segmentation in (1) in this paper can be used as the fitness function of the bee colony search algorithm and the process to get a group of optimal parameters of multi-threshold OTSU function by using bees to find the optimal nectar source is the process to find the maximum value of Formula (1). In this way, it is feasible for the artificial bee colony search algorithm to be applied in the multi-threshold image segmentation [7, 8].

3 The analysis of segmentation object

Choose 4 commonly-used standard test images: Railway, Skyscraper, Bridge, Sunshine and woods, as the images to be segmented. The following are the grey-scale histograms of the 4 images. Analyse their histogram features.

FIGURE 1 Railway

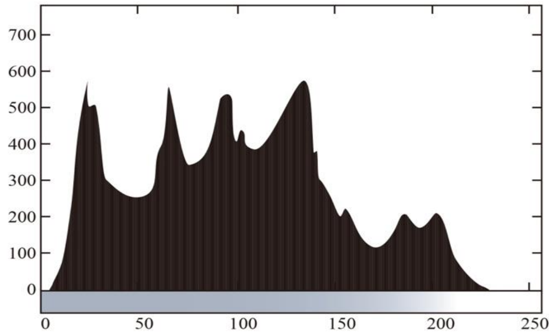


TABLE 1 The Histogram of Fig.1

FIGURE 2 Skyscraper

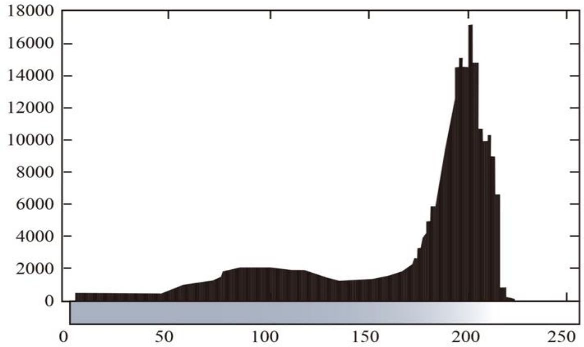


TABLE 2 The Histogram of Fig.2

FIGURE 3 Bridge

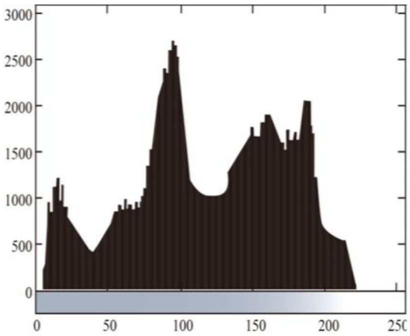


TABLE 3 The Histogram of Fig.3

FIGURE 4 Sunshine and woods

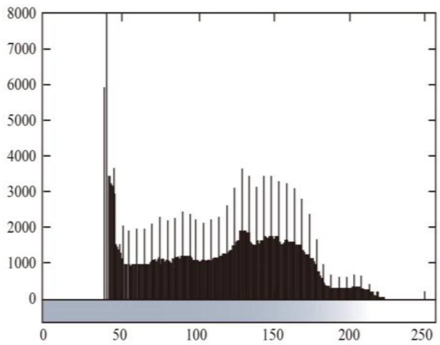


TABLE 4 The Histogram of Fig. 4

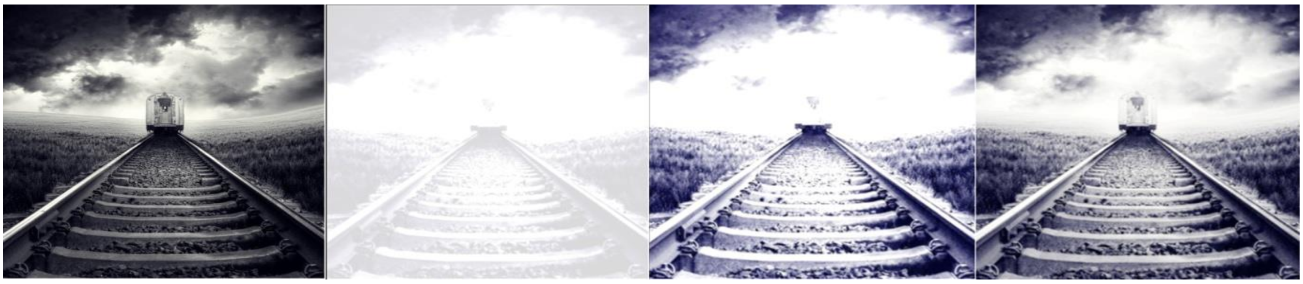
It can be seen that the histograms of the chosen standard test images from Table 1 to Table 4 have multiple peaks instead of only two peaks. The image histogram directly reflects the grey-scale distribution of the pixel points in the image; while single threshold can only segment the images with only two peaks in the histograms. Therefore, the previous single threshold segmentation method cannot precisely segment the images from Fig.1 to Fig.4 and only multi-threshold segmentation methods can be used to get ideal segmentation results.

4 Experimental analysis

In order to verify the effectiveness of DAABC in multi-threshold image segmentation, compare the performances of DAABC, PSO and basic AFSA in multi-threshold image segmentation with the above 4 standard test images as the images to be segmented and starting from the segmentation effects, segmentation speed and the quality of the optimal solutions.

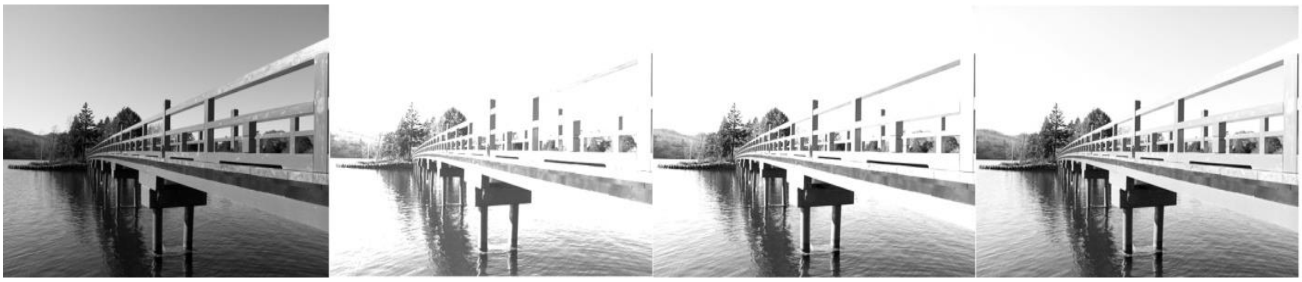
4.1 THE COMPARISON OF SEGMENTATION RESULTS

With Formula 1 as the fitness function, obtain the 3-threshold, 4-threshold and 5-threshold of the above 4 standard test images through DAABC and get their segmentation images. As indicated in Fig.7, the left are the standard test images while the rights are their 3-threshold, 4-threshold and 5-threshold segmentation images successively.



(a)Railway (b)3-Threshold segmentation (c)4-Threshold segmentation (d)5-Threshold segmentation

(e)Skyscraper (f)3-Threshold segmentation (g)4-Threshold segmentation (h)5-Threshold segmentation



(i)Bridge (j)3-Threshold segmentation (k) 4-Threshold segmentation (l)5-Threshold segmentation

(m)Sunshine and woods (n)3-Threshold segmentation (o)4-Threshold segmentation (p)5-Threshold segmentation

FIGURE 5 The results of segmentation image by DAABC

As shown in Fig.5, with the increase of the segmentation thresholds, the segmentation image is closer to the original image with better quality by integrating human visual features and comparing them with the original images. It is certain that if the threshold number of the segmentation image is closer to the number of the bottoms in the grey-scale histogram of the original images, the segmentation image is closer to the original image.

4.2 THE COMPARISON OF SEGMENTATION SPEED

In the operating environment of MATLAB, compare the performances of DAABC, PSO and AFSA in multi-threshold segmentation. Set the parameters of the 3 algorithms as follows: iterations: 50; population scale: 30 and fitness function: OTSU.

TABLE 5 The comparison of computation time of 3 swarm intelligent optimization algorithms (Unit/S)

Fig.5	M	DAABC	PSO	AFSA
(a)	3	8.5718	19.5173	13.5714
	4	10.1306	19.4181	12.8185
	5	10.7585	21.3673	15.3728
(e)	3	9.6138	19.5286	13.3185
	4	10.1582	19.6196	12.8396
	5	11.35518	20.1467	15.8179
(i)	3	10.9327	17.2868	12.5261
	4	11.6384	20.3628	15.9383
	5	10.7386	18.9515	15.2693
(m)	3	9.6281	20.7295	12.5718
	4	11.5795	19.5383	13.4156
	5	10.6215	20.3572	16.8627

Run the procedures 50 times and the time the 3 algorithms need to find the optimal threshold is as indicated in Table 7. According to this table, the order of optimization speeds of the 3 algorithms is DAABC>AFSA>PSO with the same thresholds. This is because bee colony algorithm is an algorithm of positive feedback and it is the most important link for the bees to exchange information. The dancing area is the most important information exchange place in the honeycomb. The bee dance is called swing dance. The information of the food sources is shared with other bees through swing dance in the dancing area and it leads the bees to show the yield rate of the food sources through the swing dance time; therefore, following the bees can observe many dances and choose which food source to collect the honey according to the yield rate. The yield rate is proportional to the possibility to be chosen. Therefore, the possibility the bees are recruited to a certain food source is in proportion to the yield rate of the food source. This positive feedback process leads the entire system to evolve towards the optimal solution. Therefore, positive feedback is an important characteristic of bee colony algorithm and it promotes the algorithm evolution to proceed.

It is remarkable that when segment the same image with the same algorithm of different thresholds, the time increases with the increase of thresholds because with the increase of the thresholds, the dimensions of the problems increases, thus increasing the time complexity of the algorithm.

4.3 THE COMPARISON OF QUALITY OF OPTIMAL SOLUTION

Set the same parameters as 4.2 in this paper. Run the procedures for 50 times and the results the optimal fitness function value and the optimal threshold are indicated as Table 7.

The fitness function demonstrates the difference between the target and the background. The bigger, the better. From Table 8, it can be seen that the order of the solution quality of the 3 algorithms is DAABC>AFSA>PSO on the same image with the same thresholds. Its reason is that as a parallel algorithm in nature, bee colony algorithm can be seen as a distributed multi-agent system. It has more points in the problem space and it conducts independent solution search, which not only increases the reliability of the algorithm, but also makes the algorithm have strong global search capacity. Besides, it can not only expand the search range and increase population diversity, but it is also easier to jump out of the local optimal point.

TABLE 6 The comparison of solution results of 3 swarm intelligent optimization algorithms

Fig.5	m	Fitness function value			Optimal threshold		
		DAABC	PSO	AFSA	DAABC	PSO	AFSA
(a)	3	2451.8656	2360.3573	2448.8316	57,458,383	75,63,718	63,557,381
	4	2568.3738	2578.6932	2538.6831	48,52,159,185	32,71,852,391	49,51,651,783
	5	2782.6337	2685.4873	2786.8263	45,89,736,138,663	50,95,754,134,036	47,76,652,876,275
(e)	3	2784.6583	2563.6753	2165.5647	83,674,673	94,735,456	82,874,564
	4	2254.6737	2363.2341	2356.3421	71,116,352,241	58,56,116,352	70,352,342,241
	5	2342.8741	2534.6541	2251.8652	56,54,81,643,245	18,23,81,319,377	49,37,20,341,452
(i)	3	2653.7351	2852.8361	2851.2341	65,367,465	71,85,345	61,763,875
	4	2974.3561	2867.6238	2847.6748	48,67,478,357	45,478,367,478	40,46,478,487
	5	2836.4789	2747.4879	2746.4799	45,47,479,467,278	47,46,478,783,783	51,46,467,478,478
(m)	3	2146.4799	2046.4798	2146.4748	75,367,478	57,46,457	72,467,478
	4	2673.4748	2546.4783	2367.4782	67,478,457,578	67,47,371,478	63,567,478,387
	5	2498.4673	2367.4678	2378.4789	63,46,674,467,376	61,467,467,673,987	52,76,235,765,387

5 Conclusion

This paper has introduced the dynamic adaptive bee colony algorithm into the multi-threshold image segmentation; design multi-threshold fitness function with OTSU and guides the bee colony to quickly find the optimal segmentation threshold. By testing the standard images and comparing the optimization performance of the other two swarm intelligent algorithms, the experimental results show that the algorithm in this paper has faster optimization speed and high optimization quality compared with the other two swarm intelligent algorithms on the same images to be segmented with the same thresholds.

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