Intelligent Image Segment for Material Composition Detection

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Abstract. In the process of material composition detection, the image analysis is an inevitable problem. Multilevel thresholding based OTSU method is one of the most popular image segmentation techniques. How, with the increase of the number of thresholds, the computing time increases exponentially. To overcome this problem, this paper proposed an artificial bee colony algorithm with a two-level topology. This improved artificial bee colony algorithm can quickly find out the suitable thresholds and nearly no trap into local optimal. The test results confirm it good performance.

Keywords. Image segment, artificial bee colony, material composition detection

1 Introduction

The target of image segmentation is to extract meaningful objects from the image. Segmentation is having major importance and elementary place in image processing for interpretation of any image. It is useful in discrimination an objective from some objectives or background.

In recent years, researchers proposed many methods for image segmentation. Among the existing segmentation techniques, multilevel threshold is a simple but effective tool to isolate objects of interest from the background, which required multiple threshold values to accomplish segmentation [1]. Several such methods have originally been developed for bi-level threshold and later extended to multilevel threshold described in [2]. However, all of these methods have a common problem that the computational complexity rises exponentially when extended to multilevel threshold due to the exhaustive search employed, which limits the multilevel threshold applications.

Recently, to address this concerned issue, several swarm intelligence (SI) algorithms as the powerful optimization tools have been introduced to the field of image segmentation owing to their predominant abilities of coping with complex nonlinear optimizations [3]. Among them, artificial bee colony algorithm (ABC) is one of the most popular members of the SI family, which simulates the social foraging behavior of a honeybee swarm [4]. Due to its simple arithmetic and good robustness, the ABC algorithm has been widely used in solving many numerical optimizations and engineering optimization problems. However, when solving complex multimodal problems, ABC algorithm suffers from the following drawbacks: (1) It is easily trapped into a local minimums in the early generations, which leads to low population diversity in successive generations. (2) With the dimension increasing, the information exchange of each individual is limited in a random dimension, resulting in a slow convergence rate. (3) Due to the random selection of the neighbor bee and dimensions, food sources with higher fitness are not utilized, which influences the ability of global search.

In this paper, we propose an improved artificial bee colony algorithm with a two-level topology controlling the information exchanging. The experimental results confirm it's a good performance.

The rest of the paper is organized as follows. In Section 2 the proposed hierarchical artificial bee colony is given. Section 3 presents the experimental studies of the improved artificial bee colony algorithm and the other algorithms with descriptions of the involved benchmark functions, experimental settings, and experimental results. And its application to image segmentation has been presented in Section 4. Finally, Section 5 outlines the conclusion.

2 Improved Artificial Bee Colony Algorithm

2.1 Canonical artificial bee colony algorithm

The artificial bee colony (ABC) algorithm, proposed by Karaboga in 2005 [4] and further developed by Basturk and Akay et al. [5, 6] for real-parameter optimization, which simulates the intelligent foraging behavior of a honey bee swarm, is one of the most recently introduced swarm-based optimization techniques.

The entire bee-colony contains three groups of bees: employed bees, onlookers and scouts. Employed bees explore the specific food sources; meanwhile pass the food information to onlooker bees. The number of employed bees is equal to that of food sources, in other words, each food source owns only one employed bee. Then onlooker bees choose good food sources based on the received information, and then further exploit the food near their selected food source. The food source with higher quality would have a larger opportunity to be selected by onlookers. There is a control parameter called ''*limit*'' in the canonical ABC algorithm. If a food source is not improved anymore when *limit* is exceeded, it is assumed to be abandoned by its employed bee and the employed bee associated with that food source becomes a scout to search for a new food source randomly.

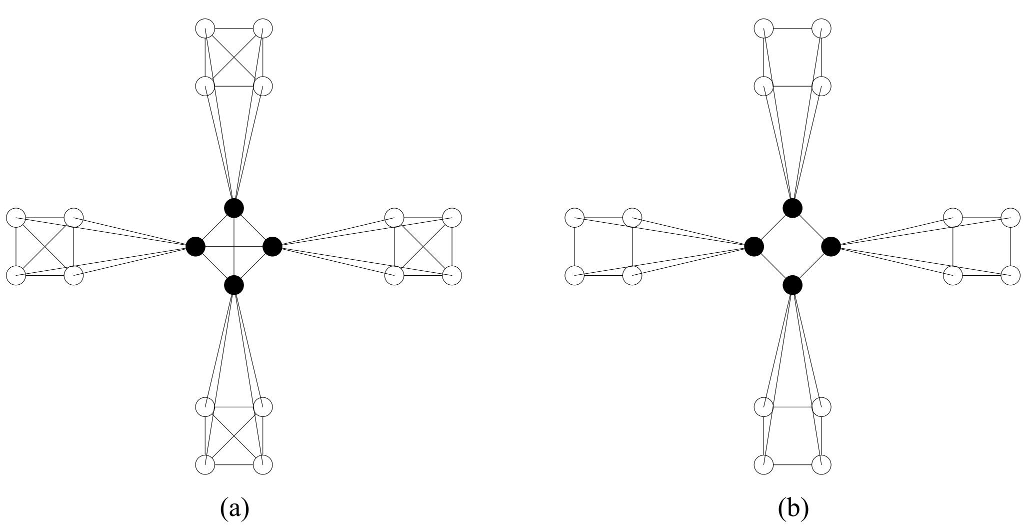

Fig. 1. Two-level interaction topologies

(a) Hierarchical star topological structure (b) Hierarchical ring topological structure

2.2 Hierarchical Artificial Bee Colony Algorithm with a Two-level Topology (HABC)

In our model, the cooperation occurred in two levels, i.e., species level (interaction between species) and individual level(interaction within species). Two hierarchical interaction topologies have been employed in this paper to realize this two-levelcooperative mechanism. In the first topology (namely the 2-level star topology, shown as in Figure 1(a)), each individualis influenced by the performance of its own species and all the other species in the ecosystem. In the second topology(namely the 2-level ring topology, shown as in Figure 1(b)), each individual is influenced only by n closest neighbours from itsown species and other n species from the ecosystem.

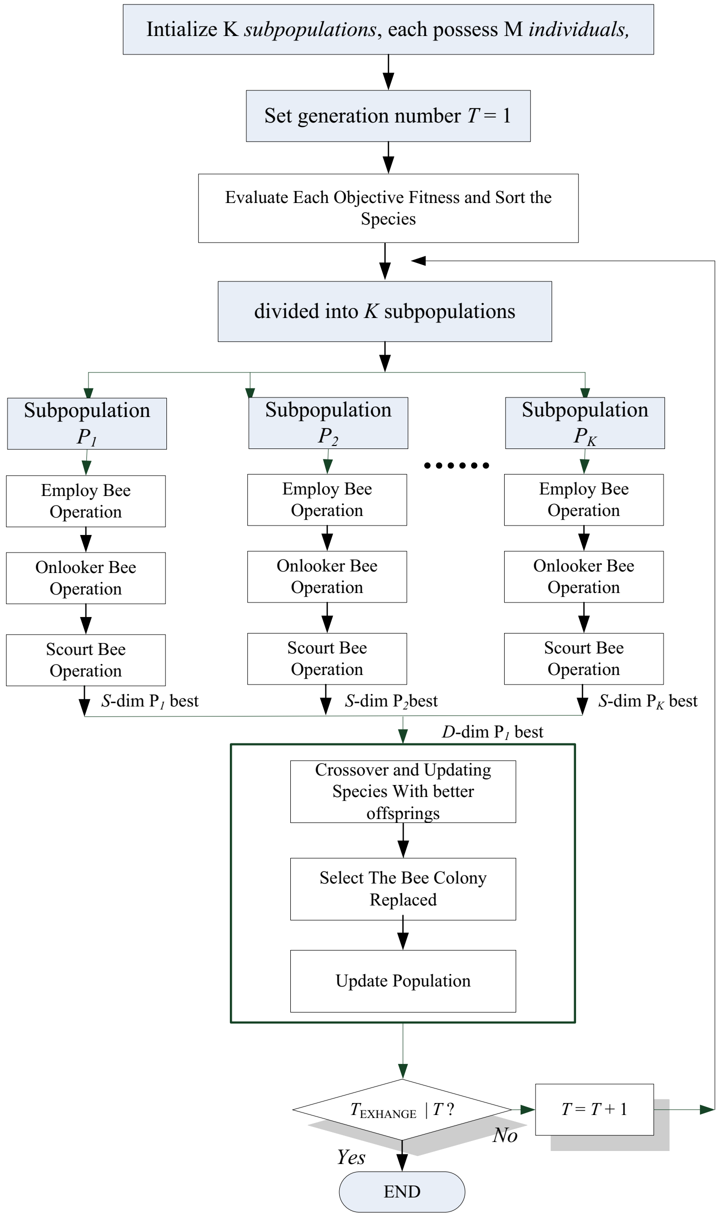

Fig.2. The flowchart of the proposed artificial bee colony algorithm

The main steps of the proposed algorithm summarized as follows: According the constraints and dimensions of the search problems, stochastically generate M species, and each species owns N individuals with D dimensions. According to the selected topological structure, determine the neighbor individuals of each individual in its own species and the neighbor species of its own species for later information communication. The flow of the proposed artificial bee colony algorithm is shown in Fig. 2.

3 Experimental study

In this experiment, we compared four variant versions of Hierarchical Artificial Bee Colony Algorithm with a Two-level Topology with the canonical ABC algorithm.

Table 1 shows the basic statistical results (i.e., the mean and standard deviations of the function values found in 30 runs) of the 30*D* benchmark test functions – griewank, rastrigin, rosenbrock and ackley. Obviously, the canonical ABC algorithm demonstrates the worse performance than other four algorithms. The ABC's variants outperform the canonical ABC algorithm. ABC algorithm with the star colony and the star swarm is comparatively good among these algorithms. The results of the ABC algorithm with the ring colony and the star swarm are also competitive. The two variants of ABC algorithm with the ring colony and the ring swarm and ABC algorithm with the star colony and the ring swarm have nearly the same results. This is attributed to that the topological structure of the upper level and lower level both with starscan improve the convergence rate.

Table 1. Results for allmulti-colony algorithms (ring) on benchmark functions

Function	Criteria D=30	ABC_ original	colony= ring swarm=star;	colony= star swarm=star;	colony= star swarm=ring	col= ring swarm=ring
griewank [-600,600]	Mean	3.5273e-002	2.0072e-002	1.6706e-002	1.8036e-002	2.9307e-002
	Best	2.0460e-002	1.2149e-002	9.9191e-004	4.6484e-003	2.1519e-009
	Worst	1.1344e-001	1.9317e-001	7.5833e-002	1.1030e-001	1.8270e-002
	Std	2.9923e-002	3.0132e-002	6.1813e-003	5.3601e-003	2.0087e-002
rastrigin [-15,15]	Mean	2.3766e+000	1.3091e+001	1.4505e+001	1.5822e+000	7.0624e+001
	Best	7.3355e-001	2.3292e-001	2.1183e+000	3.9955e-001	4.3973e-001
	Worst	8.7333e+000	6.9749e+000	2.4977e+001	7.1948e+000	1.5009e+001
	Std	2.2283e+000	2.3365e+000	6.1069e+000	2.1939e+000	3.8349e+000
rosenbrock [-15,15]	Mean	5.5504e+001	8.0374e+001	2.3365e+001	1.2928e+001	4.5391e+001
	Best	1.0025e+001	1.5002e+001	5.1353e+000	1.8746e+000	1.0252e+001
	Worst	7.5467e+001	1.7651e+002	3.4417e+001	1.9675e+001	6.7366e+001
	Std	2.0495e+001	1.1712e+002	1.1957e+001	1.0906e+001	2.5445e+001
ackley [-32.768,32.768]	Mean	4.6581e-002	3.1423e-001	1.4241e-002	9.0066e-001	3.0116e+000
	Best	5.3002e-003	5.8978e-002	2.0973e-003	4.3395e-002	9.3130e-001
	Worst	9.2545e-002	4.2501e-001	8.3362e-002	3.2369e+000	9.6034e+000
	Std	4.2248e-002	1.7765e-001	3.4167e-002	8.1111e-001	2.1700e+000

4 Multilevel threshold for image segmentation

The Otsu multi-threshold entropy measure [7] proposed by Otsu has been popularly employed in determining whether the optimal thresholdmethod can provide image segmentation with satisfactory results. Here, it is used as the objective function for theinvolved algorithms and its process can be described as follows:

Let the gray levels of a given image range over [*0, L-1*] and *h(i)* denote the occurrence of gray-level *i*.

Let

$$N = \sum_{i=0}^{L-1} h(i)\,,\, P(i) = h(i)/N \text{ for } 0 \le i \le L-1 \tag{1}$$

$$Maximize\ f(t) = w_0 w_1 (u_0 - u_1)^2 \tag{2}$$

$$\sigma(t) = w_0 \times \sigma_0^2 + w_1 \times \sigma_1^2 + \ldots w_N \times \sigma_N^2 \tag{3}$$

$$\delta_0 = \sum_{i=0}^{t-1} (i-u_0)^2 \times P_i / w_0 \quad \delta_1 = \sum_{i=t}^{L-1} (i-u_1)^2 \times P_i / w_1 \quad \delta = \sum_{i=0}^{L-1} (i-u)^2 \times P_i / w$$

$$w = \sum_{i=0}^{L-1} P_i \quad u = \sum_{i=0}^{L=1} i \times P_i / w$$

Expanding this logic to multi-level threshold

$$f_{12}(t) = w_0 \times \delta_0{}^2 + w_1 \times \delta_1{}^2 + w_2 \times \delta_2{}^2 + \ldots\ldots + w_1 \times \delta_N{}^2$$

where N is the number of thresholds. The above functionis used as the objective function to be optimized (minimized).

The experimental evaluations for segmentation performance by HABC are carried out on a wide variety of image datasets. These datasets involve a set of popular tested images used in previous studies, namely avion.ppm, house.ppm, and lena.ppm [8]. Table 2 presents the fitness function values, mean computation time, and corresponding optimal thresholds (with M-1 = 2, 3, 4) obtained by Otsu. Due to that when M-1>4 the consumption of CPU time is too long to bear, the correlative values are not listed in our experiment. It is noteworthy that the term CPU time is also an important issue in the real-time applications.

Table 2. Objective values and thresholds by the Otsu method.

Image	M-1=2		M-1=3		M-1=4	
	Objective values	Optimal thresholds	Objective values	Optimal thresholds	Objective values	Optimal thresholds
avion	3.4445E4	108,167	3.4583E4	92,146,192	3.4543E4	83,130,174,206
house	2.8486E4	106,178	2.8623E4	86,138,182	2.8576E4	72,116,155,184
lena	1.7784E4	95,156,	1.7764E4	812,129,173	1.7834E4	76,111,143,183
Mean CPU time	1.4427		61.421		2644.543	

As can be seen form Table 3, the proposed algorithm with the ring colony and the ring swarm generally performs close to the Otsu method in term of fitness value when M-1=2,3,4, whereas the performance of the improved ABC on time complexity is significantly superior to its counterpart Otsu. In other words, the proposed algorithm consumes less computing times than the traditional one. This is mainly due to the fact that the crossover-based social learning strategy used in the proposed algorithm to have faster convergence speed. Furthermore, the HABC-based algorithm achieves the best achievements among the population-based methods in most cases. This can be explained that the HABCwith two-level ring topology has a high convergence rate.

5 Conclusion

In this paper, we propose a novel hierarchical artificial bee colony algorithm with two-level topology to improve theperformance of solving complex problem. The concept and main idea is extending single artificial bee colony algorithm to hierarchical and cooperative mode by combining the multi-population cooperative co-evolution approach. The proposed algorithm is applied in solving image segmentation. Experimental results show that the proposed algorithm has a good performance on image segment for material composition detection.

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