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# Material composition detection using an image segment with an improved artificial bee colony algorithm

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In the process of material composition detection, image analysis is an inevitable problem. Multilevel thresholding based on the OTSU method is one of the most popular image segmentation techniques. The increase of the number of thresholds increases with the exponential increase in computing time. In order to overcome this problem, this paper proposes an artificial bee colony algorithm with a two-level topology. This improved artificial bee colony algorithm can quickly find the suitable thresholds without the trap of a local optimum. The test results confirm the good performance.

**Keywords:** Image segment; Artificial Bee Colony; Material Composition Detection

## INTRODUCTION

The target of image segmentation is to extract meaningful objects from the image. Segmentation is of major importance and holds an elementary place in image processing for image interpretation. It is useful in the discrimination of an objective from other objects or the 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 the objects of interest from the background, which requires multiple threshold values to achieve segmentation [1]. Several such methods have originally been developed for bi-level thresholds and later extended to multilevel thresholds as described in [2]. However, all of these methods have a common problem, that the computational complexity rises exponentially when extended to multilevel thresholds due to the exhaustive search employed, which limits the multilevel threshold applications.

Recently, to address this issue, several swarm intelligence (SI) algorithms such as 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, the 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, the ABC algorithm suffers from the following drawbacks: (1) It is easily trapped into a local minimum in early generation, which leads to a low population diversity in successive generations. (2) With the dimension increasing, the information exchange of each individual is limited to 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 global search ability.

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

The rest of the paper is organized as follows. In Section 2 the proposed hierarchical artificial bee colony is presented. 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. Its application in image segmentation has been presented in Section 4. Finally, Section 5 outlines the conclusion.

## IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

### *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, simulates the intelligent foraging behavior of a honeybee swarm, as one of the most recently introduced swarm-based optimization techniques.

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

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

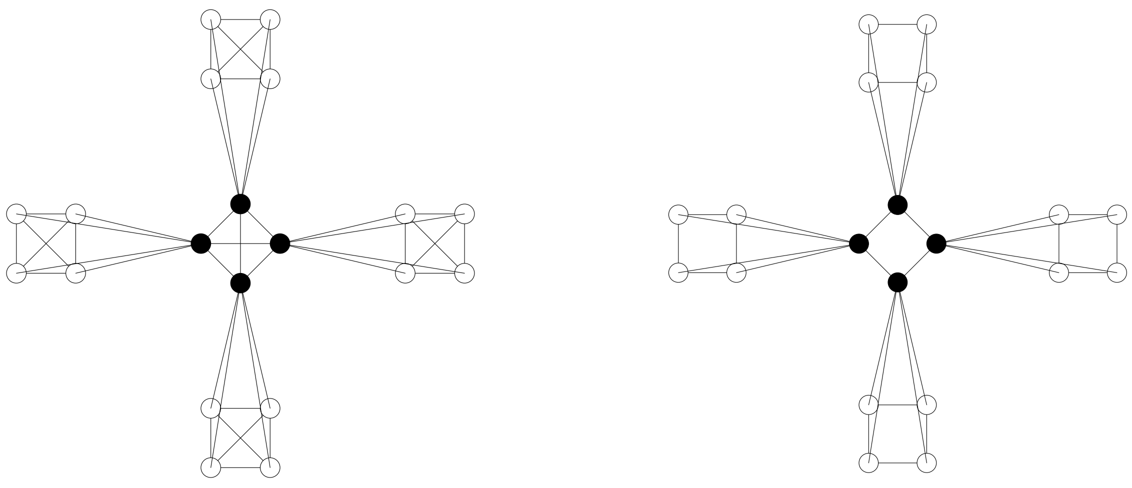
In our model, cooperation occurred at two levels, the species level (interaction between the species) and the individual level (interaction within the species). Two hierarchical interaction topologies have been employed in this paper to realize this two-level cooperative mechanism. The first topology (namely the 2-level star topology, is shown in Fig. 1(a)), each individual is 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, as shown in Fig. 1(b)), each individual is influenced only by *n* closest neighbors from its own species and the other *n* species from the ecosystem.

The main steps of the proposed algorithm are summarized as follows: In accordance with the constraints and dimensions of the search problems, the stochastically generated *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.

## EXPERIMENTAL STUDY

In this experiment, we compared four variant versions of the Hierarchical Artificial Bee Colony Algorithm with a Two-level Topology and a 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 as compared to the other four algorithms. The ABC's variants outperform the canonical ABC algorithm. The ABC algorithm with the star colony and the star swarm is comparatively good amongst these algorithms. The results of the ABC algorithm with the ring colony and the star swarm are also competitive. The two variants of the ABC algorithm with the ring colony and the ring swarm and ABC algorithm with the star colony and the ring swarm yield nearly the same results. This is attributed to the topological structure of the upper level and lower level both with a star scan to improve the convergence rate.



(a) (b)

**Fig. 1.** Two-level interaction topologies: (a) Hierarchical star topological structure (b) Hierarchical ring topological structure.

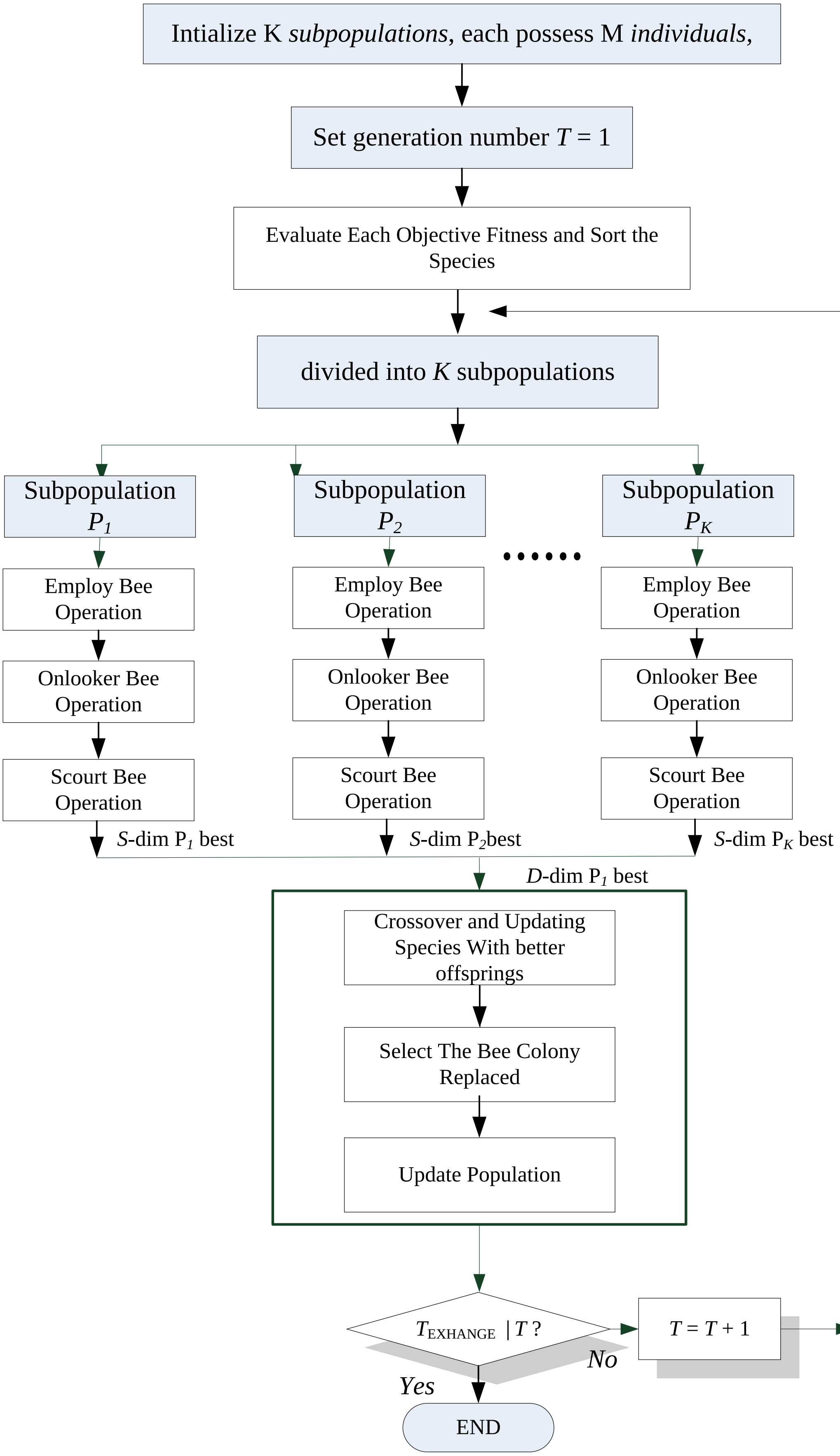



**Fig. 2.**The flowchart of the proposed artificial bee colony algorithm.

**Table 1.** Results for all multi-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 |
|---|---|---|---|---|---|---|
| | Mean | 3.5273e-002 | 2.0072e-002 | 1.6706e-002 | 1.8036e-002 | 2.9307e-002 |
| griewank | Best | 2.0460e-002 | 1.2149e-002 | 9.9191e-004 | 4.6484e-003 | 2.1519e-009 |
| [-600,600] | 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 |
| | Mean | 2.3766e+000 | 1.3091e+001 | 1.4505e+001 | 1.5822e+000 | 7.0624e+001 |
| rastrigin | Best | 7.3355e-001 | 2.3292e-001 | 2.1183e+000 | 3.9955e-001 | 4.3973e-001 |
| [-15,15] | 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 |
| | Mean | 5.5504e+001 | 8.0374e+001 | 2.3365e+001 | 1.2928e+001 | 4.5391e+001 |
| rosenbrock | Best | 1.0025e+001 | 1.5002e+001 | 5.1353e+000 | 1.8746e+000 | 1.0252e+001 |
| [-15,15] | 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 |
| | Mean | 4.6581e-002 | 3.1423e-001 | 1.4241e-002 | 9.0066e-001 | 3.0116e+000 |
| ackley | Best | 5.3002e-003 | 5.8978e-002 | 2.0973e-003 | 4.3395e-002 | 9.3130e-001 |
| [-32.768,32.768] | 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 |

**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 | |

*Multilevel threshold for image segmentation*

The Otsu multi-threshold entropy measure [7] proposed by Otsu has been popularly employed to determine whether the optimum threshold method can provide image segmentation with satisfactory results. Here, it is used as an objective function for the involved 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

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

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

$$\sigma(t) = w_0 \times \sigma_0^2 + w_1 \times \sigma_1^2 + \dots w_N \times \sigma_N^2 \quad (3)$$

$$\delta_0 = \sum_{i=0}^{t-1} (i - u_0)^2 \times P_i / w_0$$

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

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

Expand this logic to a multi-level threshold

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

where $N$ is the number of thresholds. The above function is 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 data sets. These data sets 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 optimum 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.

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

## CONCLUSION

In this paper, we propose a novel hierarchical artificial bee colony algorithm with a two-level topology to improve the performance of solving complex problems. The concept and main idea extends the single artificial bee colony algorithm to the hierarchical and cooperative mode by combining the multi-population cooperative co-evolution approach. The proposed algorithm is applied to solve image segmentation. The experimental results show that the proposed algorithm performs well to segment images for material composition detection.

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# ОПРЕДЕЛЯНЕ СТРОЕЖА НА МАТЕРИАЛИ ПО СЕГМЕНТИ НА ОБРАЗИ С ПОМОЩТА НА АЛГОРИТЪМ „ИЗКУСТВЕНА ПЧЕЛНА КОЛОНИЯ

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(Резюме)

Анализът на образи е неизбежен проблем при разкриването на строежа на материали. Един от най-популярните методи за сегментирането на образи е многостепенният OTSU-метод. С нарастване броя на степените времето за изчисления нараства експоненциално. За преодоляването на този проблем в настоящата работа се предлага алгоритъма „изкуствена пчелна колония“ с топология на две нива. Този алгоритъм може бързо да намери подходящия брой прагове, почти без попадане в локален оптимум.