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A multi-level thresholding image segmentation based on an improved artificial bee colony algorithm[☆]

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ABSTRACT

As a popular evolutionary algorithm, Artificial Bee Colony (ABC) algorithm has been successfully applied into threshold-based image segmentation. Due to its one dimension search strategy, the convergence speed of ABC is slow and its solution is acceptable but not precise. For making more fine-tuning search and further enhancing the achievements on image segmentation, we proposed an Otsu segmentation method based on a new ABC algorithm. Different from the traditional ABC strategy, our algorithm takes full use of individuals information which is defined by a focus point and the best point to increase its accuracy and convergence speed. Furtheremore, we propose an adaptive parameter to adjust the search step of individual automatically, which also improves its exploitation ability. Experimental results on Berkeley segmentation database demonstrate the effectiveness of our algorithm.

1. Introduction

Image segmentation technique is attempts to detect specific parts in an image, which is an important component in image processing, video processing and analysis [1–3]. As an important branch of image segmentation algorithm, thresholding methods segment a digital image into multiple parts. According to the number of thresholding, they have been divided into two categories: bi-level and multi-level algorithms. The former means an image should be divided into two subdivisions which use one grey value to represent its threshold. The multi-level method discriminates several distinct subdivisions from a digital image with more than one threshold. As a representative threshold-based segmentation method, Otsu [4] has attracted many researchers to do further study. Based on previous findings, the Otsu method can be treated as a maximum optimization problem. But a traditional exhausted searching method expends too much computational time to endure, especially on multi-level threshold selection of Otsu [5,6].

As a population-based algorithm, evolutionary algorithms (EAs), e.g., differential algorithm (DE) and particle swarm optimization (PSO), find a potential solution space by employing multiple individuals, which means they could achieve fast computational ability than the traditional exhausted searching methods [7–12]. As an efficient EA, artificial bee colony (ABC)

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has the characteristics of strong global search ability and steady robustness. Compared with other EAs, ABC shows a specific characteristic, i.e., one-dimension search strategy, which means bees in ABCs search the potential solutions one by one dimension. Then the global search ability of ABC is guaranteed but it should slow down its convergence rate [13,14]. In this paper, by conquering the shortcomings of the ABC algorithm, we put forward an improved ABC algorithm to solve image segmentation problem successfully.

The remainder of this paper is organized as follows. Section 2 introduces the traditional ABC algorithm in detail. Then we propose a new ABC algorithm in section 3. Otsu for multi-level thresholding image segmentation is presented in Section 4. In Section 5, experiments on Berkeley image database is conducted and an integrate conclusion is drawn in Section 6.

2. Classical ABC algorithm

ABC algorithm was first proposed by Karaboga in 2005 [15], and its essential principle is to simulate the bee's foraging behavior, with utilizes a large amount of nectar to find food sources. The algorithm consists of three types of bees, i.e., employed bees, onlooker bees and scout bees, each of which corresponds to a different search task. The main flow can be described as follows.

I. Initialization: At first, all the bees are randomly initialized in a potential solution space. The maximum and minimum boundaries of the search space are represented by *Upper, Lower* respectively. The number of food source is NP then the D-dimensional vector as $X_i=(x_{i1},x_{i2},\cdots, x_{iD})$ indicates the ith food source's position and x_{ij} denotes the jth variable of X_i, $i=1, 2, ..., NP$, $j=1, 2, ..., D$. The updating equation of initialization can be expressed as:

$$x_{ij} = Lower_{ij} + (Upper_{ij} - Lower_{ij}) * rand(0,1) \tag{1}$$

where $rand(0, 1)$ is a real number selected from the range of (0,1) randomly and uniformly.

II. Employed bees: the employed bees will exploit potential food sources by combining the previous experience and information of a randomly selected neighbor bee with Eq. (2).

$$v_{ij} = x_{ij} + \phi * (x_{ij} - x_{kj}) \tag{2}$$

where V_i is the candidate solution of i and v_{ij} represents the its jth variable; k represents the number of a neighbor bee in [1, NP]; ϕ is a uniformly distributed real value randomly selected in interval of $[-1,1]$.

Suppose that it is a minimum optimization problem, the fitness value F_i is calculated using Eq. (3).

$$F_i = \begin{cases} 1/(1+f_i) & if \quad f_i \geq 0 \\ 1+|f_i| & if \quad f_i < 0 \end{cases} \tag{3}$$

where f_i is the function value of individual i.

If the fitness of candidate solution V_i is better than that of the current solution, the current food source $X_i$will be updated by the candidate solution V_i. Otherwise X_i will remain unchanged.

III. Onlooker bees: The selection probability of each employed bee to use in the onlooker bees is calculated as

$$p_i = \frac{F_i}{\sum_1^{NP} F_i} \tag{4}$$

According to Eq. (4), onlooker bees use a roulette strategy to select a source for search by using a same updating equation as Eq. (2). The greedy selection strategy is the adopted in the onlooker bees.

IV. Scout bees: When a food source stops updating for a successive iteration, it should be selected as a scout bee and reinitialized in the solution space to replace the previous value of this food source.

3. Improved algorithm

As descripted in the second sections, ABC employs a one-dimensional update strategy, which equips the algorithm with a strong global search capability but leads to two shortcomings: unsatisfied local search ability and slow convergence speed. Specifically, the update strategy of ABC algorithm should randomly choose one dimension to learn from a selected neighbor. It may result in stagnant for individual that selects the neighbors with bad performance. Then it should waste function evaluations or lead to a low accuracy of results. To address this issue, we develop a superior learning strategy to accelerate its convergence rate and make further precise searches.

Firstly, we propose a new concept: a focus point, the definition of this point is

$$M(X)_j = median(x_{1,j}, \cdots, x_{NP,j}) \tag{5}$$

Inspired by [16] and [17], we adopt the concept of gbest which represents the best position of population ever reached. Then the food sources are updated using the following formula:

$$v_{i,j} = x_{i,j} + (M(X)_j - x_{k,j}) * (rand - 0.5) * 2 + (x_{gbest,j} - x_{i,j}) * A \tag{6}$$

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