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Novel fruit fly optimization algorithm with trend search and co-evolution

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ABSTRACT

To solve both continuous function optimization and clustering parameter problems, the novel fruit fly optimization algorithm with trend search and co-evolution (CEFOA) was proposed. It is featured with several mechanisms devised for solving the concerned problems: 1) trend search strategy was proposed and embedded into FOA. The strategy consisted two steps, which were multidimensional food evaluation method and trend search. Multidimensional food evaluation method was introduced to estimate the quality of the food sources. In the basic of the proposed method, trend search was applied to enhance the local searching capability of fruit fly swarm; 2) co-evolution mechanism was employed to avoid the premature convergence and improve the ability of global searching. To verify the performance of CEFOA we tested 26 benchmark functions with different characteristic. Experimental results indicated that CEFOA had better precision and convergence speed than several other swarm intelligence algorithms. In addition, it is applied to enhance the clustering precision and efficiency. We utilized the improved model to optimize the parameter *p* in Affinity Propagation clustering (AP). The simulation results demonstrated that AP clustering algorithm with CEFOA was prior to AP clustering algorithms with CLPSO, BLPSO and IFOA, which were the top three algorithms in precious tests. The new clustering model had more robust without setting parameter manually. Thus, the proposed algorithm had a better research potential and a good application value.

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1. Introduction

In past two decades, there have been a large number of swarm intelligent algorithms proposed. Compared to traditional optimization algorithm, such as Genetic Algorithm (GA) [1] and Artificial Immune Algorithm (AIA) [2], swarm intelligent algorithms are featured with simulating biological social intelligence behaviors to solve the optimization problems in reality. Particle Swarm Optimization algorithm (PSO) [3] simulates the bird and fish swarm. PSO algorithm has the advantages of ease-to-perform and few-parameter-settings. However, PSO algorithm is easy to be trapped in local optima [4]. Artificial Bee Colony algorithm (ABC) [5] is a simulation of a particular behavior of honeybees known as foraging behavior [6]. Cuckoo Search algorithm (CS) [7] is another nature-inspired algorithm based on the obligate brood parasitic behavior of some cuckoo species [8]. However, such algorithms are not very popular due to their high complexity [9]. The Fruit fly Optimization Algorithm (FOA) [10] is a novel swarm intelligence algorithm proposed in 2011 and its inspiration comes from cooperative foraging behaviors of fruit flies. This algorithm has superiorities of simpler model, less parameters and easier implementation [11]. FOA and its variants have a wide range of applications, such as neural network parameter optimization [12], power load forecasting [13], PID controller tuning [14], financial distress [15], multi-dimensional knapsack problem [16], steelmaking casting problem [17], web

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auction logistics service [18], joint replenishment problems [19,20], medical data classification [21], identification of dynamic protein complexes [22] and range image registration [23].

For multi-dimensional optimization problems, limited searching ability and premature convergence of basic FOA make them trap into local extreme or premature. Hence, many scholars had proposed some improved variants of FOA. Pan [11] introduced an escaping coefficient. The improved FOA not only converged quickly to the global optimal value but also had a better performance inaccuracy. In order to increase the population diversity, LGMS-based improved FOA (abbreviated as LGMS-FOA) was proposed by Shan et al. [24]. NGMS is first replaced by a linear generation mechanism of candidate solution (abbreviated as LGMS). Pan et al. [25] introduced a new control parameter to tune the search scope adaptively. A new solution generating method was developed to enhance accuracy and convergence rate of the algorithm. The simulation experiments proved the proposed IFFO significantly improves the basic fruit fly optimization algorithm in accuracy and convergence rate. By introducing the chaos theory to FOA, Mitic et al. [26] proposed a chaotic fruit fly optimization algorithm. The improved algorithm accurately reflected the potential global extreme of solution space and had a better performance in global searching. Wang et al. [19] proposed an effective and efficient FOA with level probability policy. The policy contained a level probability solution generation method and a novel parameter. The improved FOA was applied to solve the joint replenishment problems (JRPs) and made a significant result. Niu et al. [27] combined FOA with differential evolution and put forward a DE-based fruit fly ensemble algorithm (DEFOA). The DEFOA had effectively made a progress in accuracy, robustness and stability of optimization performance. Zhang et al. [9] proposed a novel multi-scale cooperative mutation fruit fly optimization algorithm (MSFOA). A multi-scale cooperative mutation mechanism was introduced to tackle the limitation of local optimum. The experimental results shown that MSFOA significantly outperforms the improved versions of FOA. Lv et al. [28] proposed an improved FOA based on hybrid location information exchange mechanism (HFOA) to improve the swarm diversity and search abilities. Experiments results on 18 complex benchmark functions indicated that HFOA outperformed main state-of-the-art algorithms. Meng and Pan [29] presented an improved fruit fly optimization algorithm. The parallel search and modified harmony search algorithm were proposed to balance search abilities and add cooperation. Numerical simulations verified that the proposed algorithm was an effective alternative for solving the MKP. Babalik et al. [30] added two sign parameters into the original FOA to broaden the search space. By analyzing experimental results, it can be said that the proposed approach achieves more successful results on many benchmark problems than the compared methods. Zheng and Wang [31] proposed a two-stage adaptive fruit fly optimization algorithm (TAFOA) to solve unrelated parallel machine scheduling problem. A heuristic was proposed to generate an initial solution which was adopted as the initial center for further evolution. Numerical comparisons were carried out to show the effectiveness of the TAFOA. Although those improved versions of FOA all enhanced search abilities and convergence speeds, it was still difficult to find the global optimal in limited iteration when facing high-dimensional problems. The objective of this paper is to deal with the drawback mentioned above.

The first contribution of this paper was to propose a novel fruit fly optimization algorithm with trend search and co-evolution (called CEFOA). In trend search strategy, Multidimensional food evaluation method and trend search were two innovations embedded into the basic FOA. Multidimensional food evaluation method was proposed to evaluate the quality of the food sources. Trend search was applied to enhance the local searching capability of fruit fly swarm and speed up the convergence rate. Co-evolution mechanism was employed to avoid the premature convergence and provide the swarm an escaping behavior. The above advanced methods were adopted to balance the population diversity and algorithm stability significantly. In order to verity the performance of the proposed algorithmCEFOA was applied to 26 benchmark functions optimization problems, including 18 basic benchmark functions and 8 expanded functions from CEC 2014 [32]. The second contribution of this paper was to use CEFOA to solve parameters optimization problem of Affinity Propagation (AP) clustering algorithm. The experimental results represented that the proposed model had advantages over clustering precision and efficiency.

The rest of this paper was organized as follows. In Section 2, the basic FOA is summarized. Section 3 describes motivation and implement of the CEFOA in detail. This study provides a convergence proof of CEFOA in Section 4. In Section 5, comparison and simulation results of 26 benchmark functions are analyzed. In Section 6, the CEFOA is used to deal with parameters optimization problems emerging from Affinity propagation clustering. The conclusions and future research are discussed in Section 7.

2. Fruit fly optimization algorithm

The basic FOA contains four interconnected phases, including initialization, osphretic searching, food sources evaluation and vision foraging. In initialization, the size of population, the termination criterion and location need to be set. An individual in a fly swarm smells the food source and flies toward that location during the osphretic searching process. The smell concentration value is evaluated for every food sources in food sources evaluation process. At the vision foraging process, the food source with the best smell concentration is found and all fruit flies will move towards the location with the best smell concentration. After that, the process of osphretic searching and vision foraging are repeated until the termination criterion is satisfied. The basic FOA can be described as follows.

2.1. Initialize the swarm location

The swarm location range (LB_j and UB_j), and the maximum number of generation (*maxgen*), the size of population (*sizepop*), and variable dimension (n) are initialized. The random fly direction and distance zone of fruit fly should be initialized as follows.

$$X_{axis} = rand(LR),$$
$$Y_{axis} = rand(LR). \tag{1}$$

where LR is the swarm location range. X_{axis} and Y_{axis} denotes the location of fruit fly having the best smell concentration value obtained during the iteration process within the current swarm.

2.2. Ophresis searching process

At the ophresis searching process, new food sources are produced randomly around the current swarm location.

$$X_i = X_{axis} + rand(LR),$$
$$Y_i = Y_{axis} + rand(LR). \tag{2}$$

where X_i and Y_i denote the location of fruit fly i.

Compute the distance of the food source to the origin by:

$$dis_i = \sqrt{X_i^2 + Y_i^2}. \tag{3}$$

2.3. Food sources evaluation process

Then compute smell concentration judgment value (S_i) and the judgment function ($Smell_i$) of the individual location as follow:

$$S_i = \frac{1}{dis_i},$$

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