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A cloud model based fruit fly optimization algorithm ☆

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ABSTRACT

Fruit Fly Optimization Algorithm (FOA) is a new global optimization algorithm inspired by the foraging behavior of fruit fly swarm. However, similar to other swarm intelligence based algorithms, FOA also has its own disadvantages. To improve the convergence performance of FOA, a normal cloud model based FOA (CMFOA) is proposed in this paper. The randomness and fuzziness of the foraging behavior of fruit fly swarm in osphresis phase is described by the normal cloud model. Moreover, an adaptive parameter strategy for Entropy *En* in normal cloud model is adopted to improve the global search ability in the early stage and to improve the accuracy of solution in the last stage. 33 benchmark functions are used to test the effectiveness of the proposed method. Numerical results show that the proposed CMFOA can obtain better or competitive performance for most test functions compared with three improved FOAs in recent literatures and seven state-of-the-arts of intelligent optimization algorithm.

1. Introduction

Swarm intelligence is a recent trend in computational intelligence and popular for the simplicity of its realizations and effectiveness of solving complex optimization problems. It is the collective behavior of decentralized and self-organized systems, natural or artificial. Various swarm intelligence based algorithms have been proposed in recent years such as particle swarm optimization (PSO) [1], artificial bee colony optimization (ABC) [2], ant colony optimization (ACO) [3], artificial fish swarm algorithm (AFSA) [4], artificial immune systems (AIS) [5], gray wolf optimizer (GWO) [6], multi-verse optimizer (MVO) [7], and ant lion optimizer (ALO) [8], etc. As stochastic optimization techniques, swarm intelligence based methods have been widely applied to many aspects in real-world application and have obtained very promising results.

Fruit Fly Optimization Algorithm (FOA), proposed by Pan in 2011 [9], is a new global optimization algorithm inspired by the foraging behavior of fruit fly. Compared with other swarm intelligence based algorithms, FOA has the advantages of being easy to understand and a simple computational process [11,12]. As a novel optimization algorithm, FOA has gained much attention and successfully applied in many areas in recent years, such as the financial distress model solving [10], the annual power load forecasting [11], analysis of the service satisfaction in web auction logistics service [12], tuning of PID controller [13,14] and fractional fuzzy-PID controller [15], neural network [16], the multidimensional knapsack problem [17], parameter identification of synchronous generator [18], and joint replenishment problems [19].

However, similar to other swarm intelligence based algorithms, FOA also has its own disadvantages. According to an empirically study in [20], the original FOA cannot solve multi-modal optimization problems effectively. To enhance the optimization performance of FOA, some researchers proposed various improved methods. Shan et al. [20] studied that FOA includes a nonlinear generation mechanism of candidate solution which limits the performance of FOA. In order to enhance the performance of FOA, the nonlinear generation mechanism of candidate solution is replaced with a linear generation mechanism of candidate solution, and then a LGMS-based improved FOA is proposed in [20]. In regards to the problem of smell concentration judgment value S is non-negative and that will restrict the application of FOA in some problem, Dai et al. [21] proposed an improved FOA by judging the location of the fruit fly in the quadrant of coordinate system. To overcome the deficiencies of non-negative fitness function, Pan [22] also proposed a modified fruit fly optimization algorithm (MFOA) which included an escape parameter that enabled it to escape from the local extreme solution to find out the global extreme solution. Moreover, since the original FOA searches for global optimal in two dimensional space, it could possibly lead to difficulties in searching for the optimal values in three-dimensional space. Hence,

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in the MFOA the original FOA was corrected and extended to the three-dimensional space. Recently, to avoid being trapped in local optimal or premature in multi-modal optimization problems, Yuan et al. [18] proposed a modified fruit fly optimization algorithm (MSFOA) with techniques of multi-swarm strategy, revised evaluation function and shrinking of exploring radius. To eliminate the drawbacks lies with fixed values of search radius of FOA, Pan et al. [23] also introduced an improved fruit fly optimization (IFFO) with a new control parameter and an effective solution generating method to improve the effectiveness of the fruit fly optimization and used it to solve high-dimensional continuous function optimization problems. One of the common modifications in MSFOA [18] and IFFO [23] is that both the distance $Dist_i$ and smell concentration judgment value S_i are removed, and the fitness function is evaluated by the decision variables directly. This modification is helpful for improving the original FOA's global convergence ability. Recently, Wang et al. [19] also proposed an improved FOA (IFOA) by introducing a method of maintaining the population diversity to enhance the exploration ability and a new parameter to avoid the acquisition of local optimal solution. Experimental results of 18 Benchmark functions and application of joint replenishment problems show that the IFOA has better comprehensive performance than the original FOA and several other competitors.

In this paper, an improved fruit fly optimization algorithm based on cloud model, namely CMFOA, is developed. In CMFOA, the normal cloud generator [24] is used to generate a new location for the fruit flies in the osphresis foraging phase. The motivation is that the foraging behavior of fruit fly swarm has features of randomness and fuzziness in the process of fruit flies learning to the best individual to fly a new promising food source. The randomness and fuzziness can be simultaneously described by the normal cloud model [25]. So, to improve the convergence performance of the FOA algorithm the normal cloud generator is used to generate new fruit fly swarms. In addition, a parameter adaptive strategy is introduced to dynamically tune the search range around the swarm location according to the evolution process. To evaluate the effectiveness of the proposed method, the CMFOA is applied to 33 benchmark functions and compared with the basic FOA and several recent variants of FOA such as MSFOA [18], MFOA [22] and IFFO [23]. Numerical results indicate that the CMFOA is able to greatly enhance the convergence performance of the original FOA. To further validate the results, the CMFOA is compared with seven representative swarm intelligence based algorithms and evolutionary algorithms such as GWO[6], MVO[7], ALO[8], CLPSO[28], IASFA[29], SGHS[30] and SaDE[31]. The results prove that the proposed algorithm is able to provide very competitive results compared to these meta-heuristics.

The rest of this paper is organized as follows. Section 2 briefly introduces the original FOA and the related works. In Section 3 the normal cloud generator is presented, then, the proposed CMFOA is presented in detail. Experimental design and numerical comparisons are illustrated in Section 4. Finally, Section 5 gives the concluding remarks.

2. Related works

In this section, the original FOA is presented firstly. Then, several recent improved FOAs that obtained impressive results are briefly discussed.

2.1. Fruit fly optimization algorithm

The FOA is a new method for searching global optimization based on the food foraging behavior of the fruit fly. Fruit flies live in the temperate and tropical climate zones, and they are superior to other species in vision and osphresis. When a fruit fly decides to go for hunting, it will fly randomly to find the location guided by a particular odor. While searching, a fruit fly also sends and receives information from its neighbors and makes comparison with the so far best location and fitness [18]. The food finding process of fruit fly is as follows: firstly, it smells the food source by using osphresis, and flies towards that location; secondly, after it gets close to the food location, the sensitive vision is also used for finding food and other fruit flies' flocking location, and then it flies towards that direction. According to the food finding procedure of fruit fly swarm, the FOA can be divided into three parts: parameters and population location initialization, osphresis search phase and vision search phase. The Pseudo-code of FOA is showed in Fig. 1.

2.1.1. Parameters and population location initialization

The main parameters of the FOA are the maximum iteration number T, the population size NP, and the random flight distance range $randValue$. The fruit fly swarm location (X_axis, Y_axis) is randomly initialized in the search space as follows.

$$X\_axis = rand * (UB - LB) + LB \tag{1}$$

$$Y\_axis = rand * (UB - LB) + LB \tag{2}$$

where $rand$ is a random function which returns a value from the uniform distribution on the interval [0, 1], the UB and LB are the upper and lower bounds of fruit fly swarm location in two-dimensional searching space, respectively.

Algorithm 1: Fruit fly optimization algorithm

```
Initialization NP, T, randValue;
Random initialization the position of population(X_axis, Y_axis);
X_i = X_axis + randValue;
Y_i = Y_axis + randValue;
Dist = sqrt(X_i^2 + Y_i^2);
S_i = 1/Dist;
Smell_i = fitness(S_i);
[bestSmell, bestIndex] = min(Smell);
smellBest = bestSmell;
X_axis = X(bestIndex);
Y_axis = Y(bestIndex);
while t < T
   X_i = X_axis + randValue;
   Y_i = Y_axis + randValue;
   Dist = sqrt(X_i^2 + Y_i^2);
   S_i = 1/Dist;
   Smell_i = fitness(S_i);
   [bestSmell, bestIndex] = min(Smell);
   if bestSmell < smellBest
      smellBest = bestSmell;
      X_axis = X(bestIndex);
      Y_axis = Y(bestIndex);
   end if
   t = t + 1;
end while
```

Fig. 1. Pseudo-code of FOA.